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FINANCIAL RATIO TIME SERIES MODELS IN DEFENSE INDUSTRIES

by

James D. Jenkins IV

December, 1994

Thesis Advisor: Douglas Moses

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FINANCIAL RATIO TIME SERIES MODELS IN DEFENSE INDUSTRIES

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Submitted in partial fulfillment
of the requirements for the degree of

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This thesis examines the forecasting ability of financial ratio time series models as applied to defense industry firms. Using previously developed descriptive models of financial ratio time series behavior, this thesis identifies plausible financial ratio forecasting models. The ability of seven different models to predict future values of financial ratios is then tested with data from defense industry firms. The results are used to answer questions concerning the accuracy and bias of forecasts and the appropriate applications of specific forecasting models. The thesis concludes that the ability of time series models to forecast future values for financial ratios depends on the specific ratio being forecast, and that the simplest model, a random walk model, is among the most useful for forecasting.

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I. INTRODUCTION

A. BACKGROUND

This thesis will examine the forecasting ability of financial ratio time series models as applied to defense industry firms.

Organizations within the Department of Defense and the Navy are frequently concerned with analysis of the financial status of private sector firms, particularly those in the defense industry. This analysis often relies on observing financial ratios to determine the financial condition of individual companies and defense industry segments. Ratio analysis techniques such as combining individual ratios to obtain summary indicators of financial well-being are used to gain insight into issues which can have long term repercussions to the Navy and Department of Defense.

The steady decline in appropriated federal spending on defense that began in the mid 1980's has had a profound effect on the defense industry environment. In the early 1980's, many firms and industry segments grew and prospered while receiving a large percentage of their sales from the Department of Defense. Questions regarding the ability of these firms to adapt and survive the current reduction in defense spending raise many areas of concern for the Department of Defense. The economic viability of defense industry firms and segments is a critical factor in decisions ranging from the award of long term acquisition contracts, to more general policy decisions such as in the development of a national strategy to maintain a viable industrial base for defense technology. Knowledge gained from accurate forecasts of the future financial well-being of defense industry entities would be an important element in making the correct decisions.

Several different theories of the behavior of financial ratios over time have been investigated over the last several decades. From the theories, different models have been derived and tested for their descriptive accuracy using historical data. This thesis will use previously developed models and test their predictive accuracy within the environment of defense contractors.

B. OBJECTIVES AND METHODOLOGY

The broad objective of this thesis is to determine the predictive ability of existing descriptive models for financial ratio time series. The thesis approach will consist of the following general steps: (1) identification of previous research on alternative theories and models describing financial ratio behavior over time, (2) selection of an appropriate defense industry sample, collection of financial data, and calculation of appropriate ratios and models, (3) computation of forecasts for ratio values and comparison of these predictions to actual ratio values, and (4) conclusions on the applicability, usefulness, and limitations of each of the forecasting models for predicting future ratio values.

C. THE RESEARCH QUESTIONS

The methodology of this thesis is designed to answer the following primary and secondary questions:

1. Primary Question

What theories and models are most useful in forecasting future values of financial ratios for defense industry firms?

2. Secondary Questions

1. What are plausible alternative forecasting models? (e.g., linear extrapolation, random walk, partial adjustment to target value).

2. What rate of adjustment is most appropriate for partial adjustment predictive models?

3. Which models are the most accurate?

4. Which models are the least biased?

5. Is a common forecast model most useful for all ratios or does the best model depend on the ratio being forecast?

6. Do particular models perform equally well during periods of industry growth or decline?

D. SCOPE, LIMITATIONS AND ASSUMPTIONS

Descriptive models developed in previous studies of financial ratio behavior over time are the basis for analysis in this study. This thesis is therefore limited to the application of existing models to forecasting future ratio values of defense industry firms using historical data. This thesis does not attempt to develop new theories describing the time series properties of financial ratios nor does it attempt to develop new descriptive models. It also does not critique the methods or approach of the previous studies from which the models are drawn, other than to summarize the studies in order to explain the evolution of the models to be analyzed. Careful scrutiny of the theoretical background for these models and of the assumptions and methodology used in their development might result in the derivation of better predictive models for financial ratio time series. Unlike most of the previous studies on ratio time series behavior which analyzed the ability of various models to explain ratio observations, this thesis attempts to assess the ability of various models to predict future ratio values.

The data used in this study is drawn from 50 of the top 100 defense industry contractors as of 1993. The data was drawn from annual reports for the years 1983 to 1992. The results of this study may therefore not be relevant to financial ratio forecasting for firms which differ dramatically from the sample. Specifically, the large size of most of the sample firms might render the results of this study inappropriate for application to much smaller firms.

Additional discussion of the results of this analysis and their application is contained in Chapter IV. Additional discussion of the sample firms chosen is contained in Chapter III.

E. LITERATURE REVIEW

Four previous studies which support three different theories of financial ratio time series behavior are reviewed in Chapter II. The earliest study, which supports a partial adjustment model with an industry mean as a target, was published by Baruch Lev in 1969. [Ref 1] A study by Y. Peles and M. Schneller published in 1989 [Ref 2], and one by H. Davis and Y. Peles published in 1993 [Ref 3], provide evidence for use of a partial adjustment model with an unknown target for description of ratio behavior. Finally, analysis in the text *Financial Statement Analysis* by G. Foster published in 1986 [Ref 4] contends that a random walk model is the most appropriate model for descriptive purposes.

F. ORGANIZATION OF STUDY

Chapter II contains further examination of the literature mentioned above, including the development of the models offered by each study, and summaries of the methods used to support the models. Chapter III is an explanation of the methodology used for analysis in this thesis. Discussion of the selection of specific models, of sample firms and data items, and of the ratios used in the analysis, is included along with a description of tests that were conducted. Chapter IV summarizes the results of the analysis. Chapter V lists the conclusions and recommendations which can be drawn from the analysis.

II. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

A. INTRODUCTION

Several studies over the past few decades have come up with distinctly different theories regarding financial ratio time series. These studies established three general models that reflect the different theories of the behavior of ratios over time. The approaches the previous studies used and the conclusions they reached provide the foundation for several of the models that will be tested in this thesis. The applicable techniques from the analysis and the three general models for financial ratio time series are discussed below.

B. TECHNIQUES COMMON TO RATIO TIME SERIES ANALYSIS

Prior to discussing the studies which investigated the behavior of ratio time series, it will be helpful to explain two mathematical procedures common to several of the studies. The techniques are that of differencing a time series, and the auto-correlation function.

1. Differencing

Differencing a time series involves calculating the difference between various elements in the time series. Most of the studies involving financial ratio time series use the first difference of the series to perform analysis.

The first differences of a time series are the differences between elements which immediately follow each other in the series. In a time series of ratios where x represents the most recent ratio value, x_{t-1} the ratio value for the period immediately preceding, x_{t-2} the value for the ratio two periods ago etc., the first differences of the series, Δx, Δx_{t-1}, ... Δx_{t-n}, are calculated: $\Delta x = (x - x_{t-1})$, $\Delta x_{t-1} = (x_{t-1} - x_{t-2}), \ldots \Delta x_{t-n} = (x_{t-n} - x_{t-n-1})$. These first differences can be related using the auto-correlation function to provide insight into the behavior of ratio series over time.

2. Auto-Correlation Function

The auto-correlation function measures the extent to which subsequent elements within a series move together. [Ref 2]. For the x_t and x_{t+j} observations, "if a higher (lower) than average observation tends to be followed by another higher (lower) than average observation j periods later, the x_t and x_{t+j} observations are said to be positively auto-correlated." [Ref 2:p. 232] Similarly if a higher value for x_t is followed by a lower than average x_{t-j} value, then these two elements are negatively auto-correlated. Common notation for the auto-correlation variable is "r." Possible values for r range from negative one to one.

The auto-correlation of first differences of a financial ratio can provide insight into the behavior of the series as it relates to theoretical models. For example, the first differences of a stationary random walk model have the theoretical property that r is equal to zero. [Ref 2: p. 232] Negative values for the auto-correlation of first differences indicate that a higher than average value for the ratio tends to be immediately followed by one lower than average, and a lower than average value followed by one higher than average. In other words, the ratio values are moving around an average value.

C. THREE MODELS FROM PREVIOUS STUDIES

The studies conducted on financial ratio time series have developed three general models to describe the ratios' theoretical behavior. Two of these models represent the larger category of ratio adjustment models. The third, the random walk model, supports its own theory of financial ratio time series behavior. The following is a description of the models and the analysis supporting their use.

1. Adjustment Models

Two of the models supported by previous studies fall under the category of adjustment models. These models theorize that a ratio value over time adjusts relative to some target value. The models differ with regards to the target value for the ratio time series.

a. *Partial Adjustment With Industry Mean Target*

Baruch Lev investigated the partial adjustment model and the appropriateness of its application to financial ratios in a study published in 1969. [Ref 1] The partial adjustment model is a common economic model, "used to examine and describe investment, inventory, and dividend decisions by firms." [Ref 1:p. 292]

The partial adjustment model as applied to financial ratios, assumes that a desirable ratio target value exists. When the value of a financial ratio deviates from the target value, the ratio will have a tendency over time to correct back toward the target value. This correction, according to Lev, would usually come from management action, such as accounting smoothing techniques or changes in business operations, but could also occur due to industry-wide effects.

Lev postulated that the target values for the ratios were the industry average values for each of the financial ratios. His model therefore defined the behavior of a specific ratio for a single firm in terms of the industry average for that ratio. Operationally, Lev used the industry average one year previous as the target for the financial ratio but discussed calculation of a more sophisticated, predicted industry average as possibly a better target value.

The basic equation for Lev's model is:

$$y_t - y_{t-1} = \beta (x_{t-1} - y_{t-1}) \tag{1}$$

where y_t is the observed value of a financial ratio at time t, y_{t-1} is the value of the ratio at time t-1, x_{t-1} is the value of the industry average for the ratio at time t-1, and beta (β) is the coefficient of adjustment where beta can range in value from zero to one.

The beta term is necessary because in spite of the hypothesized adjustment toward a target value, a ratio would not necessarily adjust fully back to the target in just one year. Nor would the period for correction be the same for all ratios. Different values of beta reflect the differing speeds of adjustment to the target for different ratios. Beta in this model is equal to 1/n, where n is the number of periods it takes for a ratio to adjust to the target. In Lev's model, the closer the beta value is to one, the faster the periodic adjustment back to the industry average target. A value of beta equal to one, indicates a complete adjustment in a single time period.

Lev then tested this model with company financial disclosures. He used historical data to fill in values for y_t, y_{t-1}, and x_{t-1}, and then used least squares regression to compute values for the beta coefficient. He checked to see if the beta computed from the least squares process indicated that the ratios were correcting to an industry average. Values of beta from zero to one were consistent with this hypothesis.

Lev concluded that the test indicated the computed beta values "strongly confirmed the periodic adjustment hypothesis." [Ref 13:p. 294] Out of 1470 individual betas computed, (Lev performed computations for six ratios of 245 firms), only 87 betas were outside the specified range. However, he also noted that the statistical significance of the computed betas as indicated by the t value were largest for the quick and current ratio and only indicated significance in about half of these values. The coefficient of determination, R^2, also was largest for the quick and current ratio but was not very large for any of the ratios.

Lev stated that because his study was designed to test the periodic adjustment hypothesis and not to examine the model's predictive capabilities, this low evidence of statistical causation was not particularly important.

Lev's study also provided insight into possible influences on the speed of adjustment. Several ratio's exhibited higher beta values, and therefore faster speeds of adjustment. Three factors which may affect the adjustment period are the cost of adjustment, the cost of being out of equilibrium, and the stability of the industry mean. The cost of adjustment indicates the degree of difficulty with which a ratio can be changed or the ability of managers to smooth the ratio back toward the target, or to alter operations to correct the ratio. The current ratio is an example of an easily corrected ratio. The cost of being out of equilibrium reflects the severity of repercussions for being out of conformance with the industry standard. For example, a low current ratio may affect the interest rates charged to a company's debt. The stability of the industry mean may affect the opinion of management on whether the difference between the firm ratio and industry ratios merely reflect an aberration in the standard or are indeed of importance.

b. Partial Adjustment With Unknown Target

Analysis by Peles-Schneller in 1989 [Ref 2] and Davis-Peles in 1991 [Ref 3] built upon Lev's application of the partial adjustment model to financial ratios. Unlike the Lev study however, the Peles and later Davis studies decided not to assume that the industry average was the target value to which the firm ratio adjusted. Rather, these later studies began with no specific value for the target and analyzed the financial ratio behavior with regard to adjustment to an unknown target value.

The Peles-Schneller study began by assuming a particular adjustment process and then "investigated whether the behavior over time of financial ratios (was) consistent with finite period adjustments." [Ref 2:p. 528] Their approach used the equation below to form a relationship between the auto-correlation of the first differences of a ratio and a term which represented the adjustment process over time.

$$r(\Delta x, \Delta x_{t-1}) = -\frac{1}{2n} \tag{2}$$

The first term in this equation represents the calculated auto-correlation between paired first differences of the ratio values. The n in the term -1/2n represents the adjustment period of the ratio. If n is equal to one, then r is equal to -1/2 and the series would revert back to its target value in one period. If n is equal to infinity, then the ratio would not correct to any target value. The term -1/2n can be rewritten as $-\beta/2$ where beta, as in the Lev study, equals 1/n. Thus the relationship can be expressed as:

$$r(\Delta x, \Delta x_{t-1}) = -\frac{\beta}{2} \tag{3}$$

Peles-Schneller first chose an arbitrary beta and calculated an estimate of the auto-correlation of the first differences, using this beta. This estimate of auto-correlation was then compared to the computed r auto-correlation value of the first differences. Statistical comparisons were made using a normal distribution, and a χ^2 goodness of fit test. The procedure was repeated for various beta values.

Peles-Schneller were then able to chose the beta value that was the best point estimate. This value was used to test their null hypotheses:

$$r = -\frac{\beta}{2} = -\frac{1}{2n} \tag{4}$$

For the six ratios they tested, they were able to come up with a beta for which they could not reject the null hypothesis. They concluded that "for all ratios tested, the behavior of the data is consistent with the existence of a finite adjustment period." [Ref 4:p. 531] The existence of a finite adjustment period for every ratio tested supports the partial adjustment model with an unknown target value.

In addition, the Peles-Schneller analysis determined adjustment periods for several ratios. These periods of adjustment concurred with common knowledge of the ease of adjustment of certain ratios. For short term ratios, the period of adjustment was relatively quick. For ratios comprised of longer term components, the adjustment periods were longer.

In a subsequent study, Davis-Peles expanded and enriched this model. [Ref 3] They removed three restrictive assumptions made in the early study: (1) that all firms have the same beta for a specific ratio, (2) that the target value remains stable over time, and (3) that there is no sampling bias in measuring the correlation coefficient. Using an analytical approach similar to the earlier Peles-Schneller study, they examined 16 ratios.

Their analysis supported the appropriateness of a partial adjustment model with a non-specific target value for several categories of ratios. The ratios were: the liquidity measures of current ratio, quick ratio, cash plus short-term investments/current assets, current asset decomposition; the performance ratios of net operating income/sales, net operating income/assets; EPS, both primary and fully diluted; equity/debt; and the gross margin ratio. For each of these ratios, their work provided a point estimate for the beta value in the model. For the ratios of equity to fixed assets, sales to fixed assets, sales to equity, and retained earnings to total assets, their work suggested that beta was equal to zero, implying that the model would not hold for these specific ratios.

2. Random Walk Model

Peles-Schneller noted that for the ratios assigned a beta value equal to zero, a random walk model would be most appropriate to describe these ratios' behavior over time. A beta value equal to zero corresponds to an r value, the auto-correlation of first differences, being equal to zero as well.

In the random walk model, a ratio value does not correct towards a target. Because the ratio is not adjusting, the best estimate of its value is the value of the ratio immediately preceding it. So the equation of the random walk model can be written simply as follows:

$$x_t=x_{t-1}+e \qquad \textbf{(5)}$$

In this equation, *e* represents an error term that is independent and identically distributed for the series. [Ref 4]

Some argument has been made that the random walk model is in fact the best predictive model for financial ratio time series. G. Foster in his text *Financial Statement Analysis* reviewed past studies and their conclusions in order to make a case for the use of a random walk model for prediction. [Ref 2] With regard to earnings time series, Foster stated that although other studies have been able to reject the random walk model for historical data, "attempts to exploit these departures from a random walk for forecasting purposes have met with limited success." [Ref 2:p. 241] He argued that just because a model is good at describing results from a past period, it is not necessarily the best model for predicting future performance. Foster contended that for some earnings ratios, such as EPS, the random walk is the best descriptive model as well.

Foster also sighted results of his own analysis on 12 financial ratio time series. The ratios were: cash plus marketable securities/total assets, current assets/current liabilities, cash flow from operations/sales, long-term liabilities/stockholders' equity, operating income/income payments, net income/stockholders' equity, sales/total assets, sales/accounts receivable, cost of goods sold/inventory, price to earnings, dividend payout, and total assets. He computed the ratios "for all firms with available data on the Compustat tape..." [Ref 2:p. 245] and then calculated auto-correlation values for both the levels of the ratios and the first differences. From the first difference auto-correlation values, Foster concluded "that a random walk model could describe the median behavior of several series..." [Ref 2: p. 245] such as operating income/interest payments and cost of goods sold/inventory.

D. SUMMARY

The random walk model and the two types of adjustment models, the partial adjustment model with industry mean target value and the partial adjustment models with other target values, are used in the analysis portion of this thesis. In addition, a simple industry average model and two trend models are included. Trend models represent another well established time series behavior theory. As stated in Chapter I, the intent of this thesis is to test the predictive abilities of previously developed models and not to check their descriptive properties. Detailed explanations of the specific models that are tested and the methods used to determine predictive capabilities are the subject of Chapter III.

III. METHODOLOGY

A. INTRODUCTION

The approach used to conduct the analysis for this thesis consisted of seven steps. The steps were: (1) identifying the sample firms and collecting the data for the sample, (2) identifying the ratios to be computed, (3) identifying the model equations to be used for forecasting, (4) determining appropriate metrics to measure model forecast error, (5) designing tests to evaluate model accuracy, (6) writing computer code in the statistical package SAS and running the program to perform computations for analysis, and (7) interpreting the output from the computer runs.

B. IDENTIFICATION OF SAMPLE AND DATA COLLECTION

1. Sample Identification

The sample used for the analysis in this thesis consisted of 50 of the top 100 defense contractors as of 1992. The primary question of this thesis concerns the forecasting ability of established financial ratio time series models within the context of defense industries. The first step in starting analysis was to identify a suitable sample of defense firms. The preliminary concerns in completing this step included identifying what factors would be used to delineate "defense firms," deciding on the number of firms to include, and choosing firms which represented a broad spectrum of the segments within the defense industry.

To identify defense firms, a list from *Defense 93 Almanac* for the top 100 defense contractors was used as a reference. [Ref 5] The list ranks defense companies by the dollar volume received from prime contract award from the Department of Defense. Although other statistics, such as companies receiving the largest percentage of their income from the Department of Defense, could have been used to identify a population, such statistics would have resulted in questions concerning exclusion of some firms based on the disparate size of their operations. The list based on dollar volume of prime contract awards resulted in a sample of firms that was relatively homogeneous in size, (all were relatively large firms). In addition, the list covered a broad spectrum of the industry segments within defense as desired.

From the list of 100 firms, 50 were chosen for the sample. The list of these 50 firms is included in Appendix A. This number of firms was arbitrary but was chosen to provide for the adequate inclusion over the spectrum of defense industry segments while considering time constraints in data collection. The primary factor in deciding on which firms to include from the list was the ability of the firms to provide data in the form of annual reports for the years in which the analysis was to be carried out. Although all of the 50 firms finally chosen for the sample did not provide annual reports for every year, they were able to provide the most data out of the top 100 firms. This method resulted in a sample of 50 firms that covered a broad spectrum of segments of the defense industries and that fit the thesis description of defense firms.

2. Data Identification and Collection

a. *Time Period for Data Collection*

Data were collected for the 50 firms for the ten year period from 1983 through 1992. This period was chosen to provide a satisfactory range of data for comparison of actual ratio values to those forecasted using model calculations. The period beginning in 1983 was chosen both for ease of obtaining sources for data and to allow analysis over a period representative of modern economic conditions. Although a ten year period of financial data is brief when compared to periods used in other studies, the data provided adequate observations to thoroughly test ratio forecasts against actual ratio values. The shorter period of time included in this study also helped to limit the impact of factors which can affect analysis of financial data over time. Some of these issues are discussed briefly below.

Collection of financial data over time can be problematic due to the dynamic nature of the economic environment. Accounting method changes, accounting classification changes, and structural changes, such as changes in government regulation, competition, technology, and acquisition and divestiture, will affect the consistency of data for individual firms and for industries over time. The longer the time period over which the data is collected, the more certain and the more profound the affect on the consistency and comparability of reported financial data.

Chapter 7 of the text *Financial Statement Analysis* by G. Foster contains a comprehensive explanation of issues of analyzing time series data from financial reports. [Ref 4] An in depth examination of such issues is not germane to the topic of this thesis. However, it is relevant to note that for all of the above changes which potentially affect financial data consistency over time, one option Foster suggests to deal with the effects of the changes is simply to use the data as reported. His primary argument supporting this option is that in many specific cases the effect of these changes on the financial data reported is immaterial to the figures as a whole. [Ref 4]

For this thesis, data was collected as reported in financial statements, without manipulation to counter the affect of changes over time. When faced with differences in structure, accounting methods, or classification, the affect on the financial data reported was almost always deemed immaterial. This was due primarily to two factors. First, the large size of the sample firms' operations rendered the affect of most of these changes relatively unimportant.

Second, the shorter time period under consideration minimized the number of changes which came into play. In a few instances, changes resulted in visibly inconsistent data. In such cases the data for these periods was simply excluded from the sample data. An example of this was the 1983 financial data from AT&T which was inconsistent with later years due to the break up of the company into smaller business entities.

b. Selection of Data Items

Data items were chosen to provide for calculation of a wide range of ratios. Twenty-nine specific items from annual report balance sheets, income statements, statement of cash flows, and explanatory notes were collected for every year for each firm. As stated above, not all firms were able to provide annual reports for all years, and Moody's Industrial Manual was used to fill in this missing data.

Following data collection, data was input to a SAS data base on an Amdahl 5990 Mainframe with IBM VM/CMS operating system. Consistency tests were run on the data to identify possible incorrect outliers and other data problems. During these checks, several problems were noted with values from the statements of cash flows. The values were traced back to the source financial reports. Some of the cash flow items were found to have been drawn incorrectly from the varying reporting formats of different companies over the ten year period. It was determined that the cash flow data items were too unreliable and they were excluded from further analysis. Earnings per share values in the data base were also determined to be inconsistent after tracing back to the source documents and were excluded as well.

C. RATIOS CHOSEN FOR ANALYSIS

Ratio items for analysis were chosen to satisfy several criteria. They were to be representative of the financial ratio categories of liquidity, profitability, asset management, and debt management. They were to be drawn, when possible, from those ratios used consistently in previous studies. They were also chosen as per their common usage in financial management.

The list of ratios that were chosen for analysis using these criteria were:

1. Liquidity Ratios:
   a. Current Ratio = Current Assets/Current Liabilities
   b. Quick Ratio =
      (Current Assets - Inventory)/Current Liabilities
   c. Working Capital/Total Assets =
      (Current Assets - Current Liabilities)/Total Assets
2. Asset Management Ratios:
   a. Total Asset Turnover = Sales/Total Assets
   b. Inventory Turnover = Sales/Inventory
   c. Receivables Turnover = Sales/Accounts Receivable
3. Profitability Ratios:
   a. Return on Total Assets =
      Total Income from Operations/Total Assets
   b. Return on Stockholders' Equity =
      Total Income from Operations/Stockholders' Equity
   c. Return on Sales = Total Income from Operations/Sales
4. Debt Management Ratios:
   a. Equity/Total Liabilities
   b. Total Liabilities/Total Assets
   c. Interest Coverage =
      (Total Income + Interest Expense)/Interest Expense

Six of these ratios were included in two or more of the studies reviewed for this thesis. The ratios are all commonly used for financial management applications and they uniformly cover the general categories of ratios desired.

D. DESCRIPTION OF MODELS FOR ANALYSIS

The process for selecting specific model equations to be tested was guided by the previously reviewed studies on financial ratio time series behavior. Equations were derived that represented the random walk model, the industry average model, and the two types of adjustment models supported in previous studies. Equations were also derived to test the predictive ability of trend models, another well established category of time series model that juxtapose those mentioned in the reviewed studies. The specific equations for the models and explanations of their derivation are included below.

1. Random Walk Model

The random walk model is the simplest model to write in terms of a testable equation. The random walk model theorizes that a ratio does not follow any trend or adjustment process over time. The theoretical, descriptive form of the random walk model is:

$$x_t=x_{t-1}+e \qquad \textbf{(6)}$$

where x_t represents the current value of the ratio, x_{t-1} represents the value of the ratio in the period immediately preceding, and e represents an error term. Because the error term changes over time according to some probability law and not through a deterministic process [Ref 4], it cannot be predicted and therefore cannot be included in a predictive model. The best predictor of the future value of a ratio therefore, is the value of the ratio in the period immediately preceding. The equation derived for testing the random walk model was:

$$r_f = r_{t-1} \tag{7}$$

The r_f term represents the ratio value forecast for the period. The r_{t-1} term represents the ratio value in the period immediately preceding the forecast period.

2. Industry Average Model

The industry average model is another simple model to put into a testable equation. The industry average model hypothesizes that a firm's ratio value will directly follow the industry average for that ratio. It assumes that firms adjust their ratios to the average level of other firms in the industry. The best predictor for the ratio value is the industry average for that ratio in the period preceding the forecast. The equation derived for the industry average model was:

$$r_f = I_{avgt-1} \tag{8}$$

The I_{avgt-1} variable represents the industry average for the ratio being forecast in the preceding period. To arrive at this average, the value for the ratio in question was calculated for every firm in the sample for the period previous to the forecast period. These ratios were then averaged to give a mean industry ratio value which became the target for the forecast period. The industry average model will be referred to in future text as the simple industry average model to distinguish it from other models with similar names.

3. Partial Adjustment Models

Adjustment models, or models of reversion to a central tendency, theorize that ratios adjust in relation to a target value over time. The two general models discussed in Chapter II that represent this category were the partial adjustment model with the industry average as a target, and the partial adjustment model with an unknown target. These models describe ratio time series as a corrective process. If individual ratio values are driven away from the central tendency or target, future values will tend to correct back towards the target value.

Although a ratio value above or below the target value reverts back towards this central tendency over time, the adjustment process is not necessarily completed in one period. The adjustment process in the next time period may only be a partial adjustment, as the names assigned these models suggest.

The general form of a predictive equation for an adjustment model forecasts the value of the ratio based on the previous period's ratio value plus some portion of the difference between the previous period's ratio value and the target value. In other words the general form for this equation is:

$$r_f=r_{t-1}+\beta(target_{t-1}-r_{t-1}) \tag{9}$$

The r_f and r_{t-1} terms are the same as in the random walk model. The target is the central tendency chosen for the specific model, and will therefore be calculated differently for different models. The beta term determines the amount of correction back towards the target value in the forecast period. If beta is equal to one, the forecast ratio adjusts completely back to the target value in one period. If beta is equal to 1/2, the forecast ratio adjust only halfway back to the target value in one period.

a. *Industry Average Target*

The equation derived to test the partial adjustment model with the industry mean as the target value was:

$$r_f=r_{t-1}+\beta(I_{avgt-1}-r_{t-1}) \tag{10}$$

The variables in this model are as described for the previous models. This model assumes that firms adjust ratios to the average level in the industry but that the adjustment is only partially completed in any period. The partial adjustment model with industry average target will be referred to in future text as the industry average adjustment model.

b. Unknown Target Value

As described in Chapter II, the descriptive model for this theory was established by demonstrating that an adjustment process for a ratio time series was occurring. The analysis of the descriptive model did not require the identification of the ratio target value. In order to test the predictive ability of this model, some target value had to be chosen so that a forecast ratio value could be calculated.

Although a variety of target values could have been chosen, this thesis used two commonly referenced standards as targets in the model. The target values chosen were a firm moving average target and a fixed deviation from the industry average target. Their common usage made them good choices to provide for a practical, though not exhaustive, test of the partial adjustment with unknown target model of ratio time series behavior.

(1) Firm Moving Average Target. The firm moving average target was calculated by finding the average of the firm's ratio values for the three periods preceding the forecast period. The equation derived for the partial adjustment model with a firm moving average target was:

$$r_f = r_{t-1} + \beta \times \left(\frac{r_{t-1} + r_{t-2} + r_{t-3}}{3} - r_{t-1} \right) \qquad \textbf{(11)}$$

This equation indicates that the firm's target ratio value is determined by its own mean ratio value over the last three years. This model assumes that firms attempt to achieve a stable value for a ratio, as represented by recent levels for that ratio, and adjust deviations back to that value. The partial adjustment model with a moving average target will be referred to as the moving average adjustment model.

(2) Fixed Deviation Target. The target value for the fixed deviation model was calculated by determining the average amount a firm's ratio value had deviated from the industry average over the previous three years. This deviation was then multiplied by industry average for the ratio in the year preceding the forecast. This two step process for calculating the target is summarized in the equation below:

$$T_{t-1} = I_{avgt-1} \times \frac{\frac{r_{t-1}}{I_{avgt-1}} + \frac{r_{t-2}}{I_{avgt-2}} + \frac{r_{t-3}}{I_{avgt-3}}}{3} \tag{12}$$

Using this target value the equation derived for the partial adjustment model with a fixed deviation from the industry average for target was:

$$r_f = r_{t-1} + \beta\,(T_{t-1} - r_{t-1}) \tag{13}$$

This model indicates that a firms ratio target is a value some fixed deviation from the industry average in the previous period. This model also assumes that firms attempt to achieve a stable value for a ratio, but that value is set relative to the industry. For example, a firm may set a policy of maintaining less leverage or greater liquidity than the industry. The partial adjustment model with a fixed deviation target will be referred to as the fixed deviation adjustment model.

4. Trend Models

Trend models assume that a firm's ratio value will continue to follow an established trend over time, in contrast to the adjustment models. Although trend models were not addressed in the literature reviewed for this thesis, they include many common time series forecasting methods. They also serve to test an opposing theory of established time series behavior from the adjustment model. Results from their forecast can therefore be used not only to judge the ability of the trend models to forecast ratio values, but also to provide additional information regarding the application of adjustment models for prediction.

a. Firm Linear Extrapolation Model

The firm linear extrapolation model derives the trend for a ratio from the firm's own previous ratio values and then extrapolates that trend into the future to make a forecast. A trend or expected change is calculated by examining the historical change between periods. This expected change is then added to the previous period's ratio value to arrive at the forecast. The forecasting equation used for analysis of the linear extrapolation model was:

$$r_f=r_{t-1}+\frac{(r_{t-1}-r_{t-2})+(r_{t-2}-r_{t-3})+(r_{t-3}-r_{t-4})}{3} \tag{14}$$

In this equation the trend, or expected change is calculated by finding the average of the first differences for the three periods preceding the forecast, and this expected change is added to the previous period's ratio value. This model assumes that the firm's ratios will change in the future as determined by the firm's historical periodic ratio changes. In other words the firm is striving to continue its own historical ratio trend. The linear extrapolation model will be referred to in future test as the firm trend model.

b. Industry Linear Extrapolation Model

The industry linear extrapolation model derives its trend or expected change based on the industry average's historical change in ratio value. The equation derived to test this model was:

$$r_f=r_{t-1}+\frac{(I_{avgt-1}-I_{avgt-2})+(I_{avgt-2}-I_{avgt-3})+(I_{avgt-3}-I_{avgt-4})}{3} \tag{15}$$

The industry trend is calculated similar to the firm trend, by finding the average of the first differences of the industry average ratio values for the previous three periods. This expected change is then added on to the firm's ratio value for the period preceding the forecast.

This model assumes that the firm's ratio value will be determined by a trend established by the industry. In other words, the firm will strive to follow the industry average's historical trend. The industry linear extrapolation model will be referred to as the industry trend model.

E. DETERMINATION OF METRICS TO MEASURE ERROR

Prior to calculating the forecast ratio values from the model equations, suitable methods for error calculations needed to be chosen. The metrics chosen needed to provide a method of determining both the accuracy of the forecast values, and their bias. The metrics also needed to summarize the error calculations into comprehensive composite measures of error that provided a basis of comparison between the forecasting equations. Two error calculations, the Mean Absolute Percentage Error (MAPE) and the Mean Percentage Error (MPE), were chosen. Their selection is supported by common usage in many texts concerning forecasting models and error calculation such as in Chapter 28 of *The Handbook of Forecasting, A Manager's Guide*. [Ref 6]

To determine the accuracy of the forecast, the Absolute Percentage Error (APE) was calculated for each ratio forecast. The formula used to calculate this error was:

$$APE=\frac{|r_t-r_f|}{r_t} \qquad \textbf{(16)}$$

where r_t was the actual ratio value for period, and r_f was the forecast ratio value for the period.

These individual accuracy measures were then averaged for the years 1987 through 1992 ratio by ratio to calculate the Mean Absolute Percentage Error (MAPE) for the forecasting equation for each ratio. Calculations of the average errors were based on only the last five years of data to provide a consistent basis for comparison between all models. (Although some models could provide forecasts for years from 1984 through 1992, other models were limited to only the years 1987 through 1992.) The composite error measurements therefore, included only these five years of error calculations.

For example, a MAPE was determined for the random walk model's forecasts for the current ratio. This random walk, current ratio MAPE consisted of the average of the absolute errors for each of the current ratio values forecast by the random walk model for the years 1987 through 1992.

To determine the bias of the forecast, the Percentage Error (PE) was calculated. The formula for this error measure was:

$$PE=\frac{r_t-r_f}{r_t} \tag{17}$$

These individual error measures were also averaged over the years 1987 through 1992 to determine the Mean Percentage Error (MPE) for each forecasting equation for each ratio.

The order of the variables in the PE equation results in a negative value for MPE when the forecast from the models are positively biased. This is because when the forecast ratio value, r_f, is greater than the actual ratio value, r_t, the PE error calculations produce a negative error value. Conversely, a positive value for MPE indicates a negative bias in the model forecasts. The sign of the MPE can thus be observed to determine whether a model tends to under predict future ratio values, (indicated by a positive value), or over predict, (indicated by a negative value).

F. GENERAL TEST PROCEDURES TO EVALUATE MODELS

The tests used to evaluate model forecasting ability were established after derivation of the model forecasting equations. The test procedures consisted first of computing the values for the 12 ratios for every year for every firm. These ratio values were then used as inputs to the forecasting equations to arrive at forecasts for every ratio and every year for which the data and models allowed. The Absolute Percentage Error and Percentage Error were calculated for every ratio for every year.

Individual error computations were aggregated to come up with 12 Mean Absolute Percentage Errors and 12 Mean Percentage Errors, (one for each ratio), for each forecasting equation. Results of these error computations along with other parts of the computer output were analyzed to draw conclusions to answer the thesis questions. The detailed steps required to answer each thesis question are contained in Chapter IV.

G. DATA ITEMS OUT OF RANGE

Some of the data items which were to be used to compute the 12 ratio values were out of acceptable ranges, despite having been accurately collected from financial reports. This occurred for a variety reasons including changes in accounting principles and reporting formats, and one time extraordinary losses or charges. Data values for stockholder's equity, interest expense, current liabilities, total liabilities, and inventory that were less than or equal to zero, if used to compute ratios, would have resulted in nonsensical ratio values and in misleading forecasts and error computations.

To deal with this problem, when the above data items were less than or equal to zero, a "." was inserted to indicate that the data item was missing. Computations performed on such a missing data item resulted in the SAS program reporting a missing value for the computed item.

H. SUMMARY

After all forecasts and summary errors were computed, the final step in the analysis was to group the output and interpret it to answer the thesis questions. A summary of the procedures used to carry out tests specific to each thesis question, summary output from the test runs, and the interpretation of this output as applied toward the thesis questions are all contained in Chapter IV.

IV. ANALYSIS

A. INTRODUCTION

After using the SAS program to forecast all twelve ratios for every model equation and then calculating the composite error measures, error results were grouped and analyzed in order to answer the thesis questions. The specific procedures used to analyze the error measures and to arrive at answers for each thesis question are discussed in this Chapter and organized as follows.

Section B addresses the thesis question concerning the optimum beta value for partial adjustment models. Section C provides a detailed account of the numerical results of the forecasting analysis. The model performance in terms of accuracy and bias error are listed ratio by ratio, with summaries of the forecast results included at the end of each ratio category. Section D addresses the specific thesis questions on model accuracy and bias. Section E addresses the question of model performance in periods of growth and decline.

B. CALCULATING BETA FOR PARTIAL ADJUSTMENT MODELS

Before a valid comparison of the forecasting ability of the seven model equations could be made, the optimum beta for the partial adjustment models had to be chosen. One possible method to select the beta would simply have been to choose one value out of the literature for all partial adjustment models. However, the choice of beta might have affected the predictive ability of these models. The different partial adjustment models also might have forecast most accurately using different betas. A separate analysis step was therefore carried out to determine what beta values to use for each model. Because the partial adjustment model forecasts could be affected by which beta was chosen, the outcome of the comparison of model predictions might also have been affected by this initial analysis.

1. Test Procedures

The three partial adjustment models were analyzed independently in order to determine the best beta for each model. The independent analysis was not carried through the point of choosing the best beta for each ratio forecast for each model. Such analysis could have resulted in different betas for every ratio for every model, or essentially in 36 "different" partial adjustment model equations, instead of the three this thesis investigated.

Forecast were made for all ratios using the three models and different beta values. The beta values tested were: 1, .75, .5, .4, .3, .2, .1, and 0. The error measures for the different model forecasts using the different betas were then compared. The beta value which resulted in the "best" composite error measures for each model was chosen as the beta for that model equation.

2. Results

The analysis to determine the best beta for each model equation resulted in the choice of the same beta for all models. For all three partial adjustment models, the best beta in terms of forecasting over the spectrum of all twelve ratios was a beta equal to zero. This held true when both the accuracy measure of Mean Absolute Percentage Error (MAPE) and the bias measure of Mean Percentage Error (MPE) were considered.

Table 4.1 lists the beta values for the industry average adjustment model forecasts which resulted in the best MAPE and MPE, i.e. the MAPE with the lowest value, and the MPE with the value closest to 0.

Ratio	Best β as indicated by MAPE	Best β as indicated by MPE
Current	0	0
Quick	.1	0
Working Capital to Total Assets	.1	.2
Total Asset Turnover	0	.4 or 0
Inventory Turnover	0	0
Receivables Turnover	0	0
Return on Total Assets	.2	0
Return on Stockholder's Equity	.75	.2
Return on Sales	.3	.1
Equity to Debt	0	0
Debt to Total Assets	0	.3
Interest Coverage	.1	.1

Table 4.1 Optimal Betas for Industry Average Adjustment Model Forecasts

Table 4.2 lists the optimal beta values for the moving average adjustment model forecasts as determined by MAPE and MPE.

Ratio	Best β as indicated by MAPE	Best β as indicated by MPE
Current	.1	0
Quick	.2	0
Working Capital to Total Assets	1	.75
Total Asset Turnover	0	0
Inventory Turnover	.1	1
Receivables Turnover	0	0
Return on Total Assets	.1	0
Return on Stockholder's Equity	.3	.3
Return on Sales	.1	0
Equity to Debt	0	0
Debt to Total Assets	0	0
Interest Coverage	.2	.2

Table 4.2 Optimal Betas for Moving Average Adjustment Model Forecasts

Table 4.3 lists the optimal beta values for the fixed deviation adjustment model forecasts as determined by MAPE and MPE.

Ratio	Best β as indicated by MAPE	Best β as indicated by MPE
Current	.1	0
Quick	.2	0
Working Capital to Total Assets	1	.75
Total Asset Turnover	0	0
Inventory Turnover	.1	0
Receivables Turnover	0	0
Return on Total Assets	.1	0
Return on Stockholder's Equity	.4	.3
Return on Sales	.1	0
Equity to Debt	0	0
Debt to Total Assets	0	1
Interest Coverage	.2	.2

Table 4.3 Optimal Betas for Fixed Deviation Adjustment Model Forecasts

The MPE's from the forecasts indicate that for at least seven of the 12 ratios, the least biased models had a beta equal to zero. In the case of one model the MAPE was minimized for six of 12 ratios, and for the other two models for four of 12 ratios, when a beta equal to zero was used. For the majority of instances where a non-zero beta minimized the MAPE for ratio forecasts, a beta of .1 was the best value.

3. Selecting the "Best" Beta for Future Tests

Strict adherence to the planned methodology for choosing a beta value would have resulted in choosing a beta equal to zero. This was an unsatisfactory choice for a beta value. If a zero beta value was used, these three partial adjustment models would be turned into identical random walk models. The partial adjustment portion of their equations would be zeroed out due to multiplication by the beta term.

In order to retain these models for the analysis yet to be conducted, a beta value of .25 was chosen for all models. This value was chosen for three reasons. First, the research conducted by Davis and Peles calculated a beta, for large firms with a non-specific target adjustment process, of approximately .25 for the quick, current, and cash plus short term investments/current asset ratios. Second, with the exception of forecasts for two ratios, the optimum non-zero betas indicated by the forecasting error calculations ranged from .1 to .3. Finally, a value of .25 for beta would indicate that a firm adjusted one quarter of the way back towards the target value in a single period. This beta was deemed to be the smallest non-zero beta value that still would justify the models in question being designated as partial adjustment models vice random walk models. Of course, the indication that for most ratios, a beta equal to zero provided the best forecasts for the partial adjustment models provided some preliminary insight into the predictive ability of these three models for the future forecasting analysis.

4. Additional Findings

The trend behavior for the industry average adjustment model with beta varied from one to zero is illustrated in Figures 4.1 through 4.4 on the following four pages. The MPE and MAPE are broken up into two graphs each with six ratios per graph to provide a better level of detail for the illustrations. The forecasts are grouped on pages by the amount of error to provide the best scale for the Y axis of the graphs. The abbreviations used for the ratios on the graph legends are: current ratio, CURRAT, quick ratio, QIKRAT, working capital to total assets, WCTA, total asset turnover, TATN, inventory turnover, INVTN, receivables turnover, RECTN, return on total assets, ROTA, return on stockholder's equity, ROSE, return on sales, ROSA, equity to total liabilities, EQTDBT, total liabilities to total assets, DBTTA, and interest coverage, INTCOV.

Changing the beta values for each model resulted in consistent trends of predictive ability. For example, when the optimal beta value was zero, varying the beta values from zero up to one resulted in consistently worse forecasts.

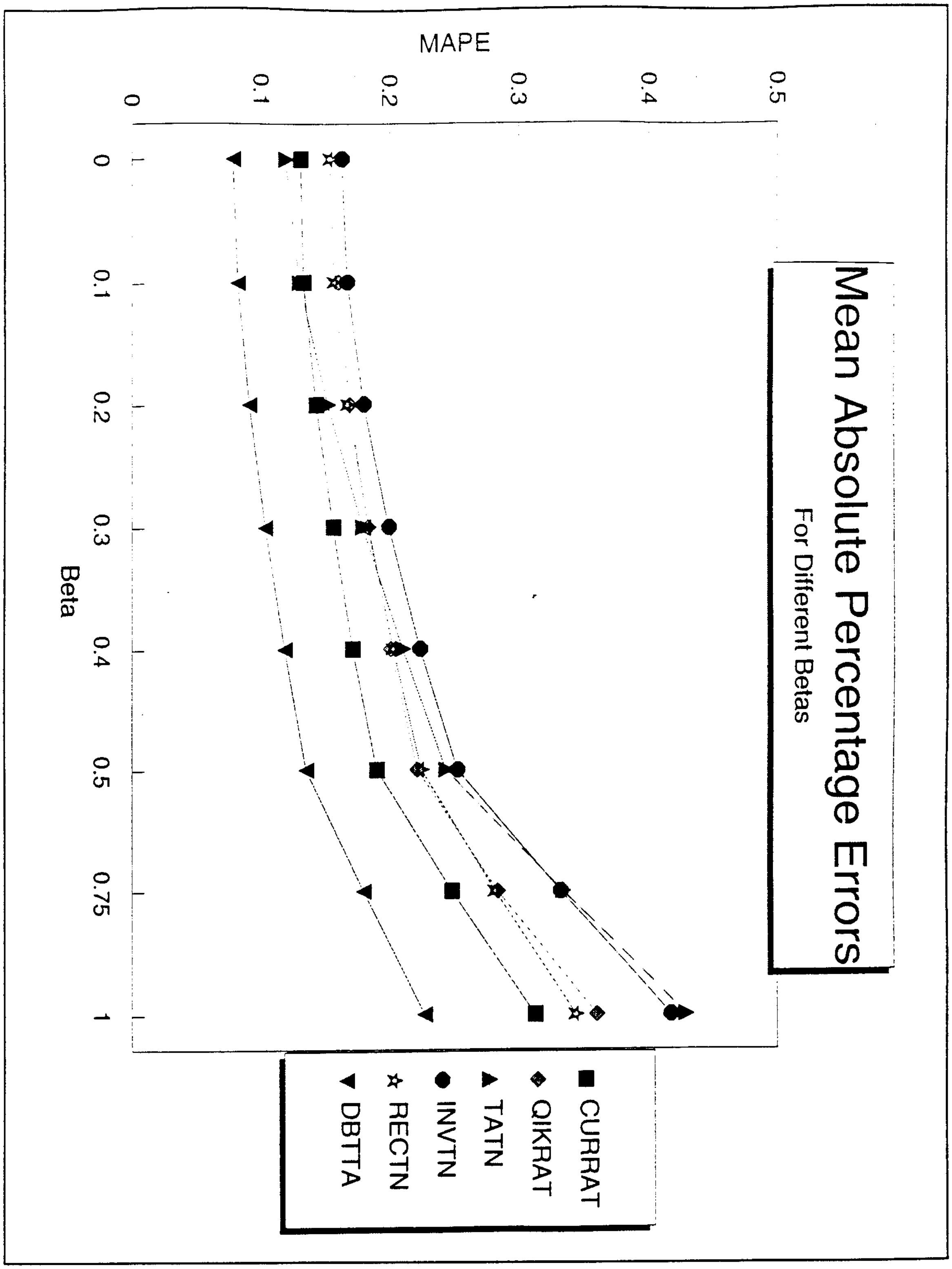

Figure 4.1 MAPE's from Industry Average Adjustment Model Forecasts for Various Betas

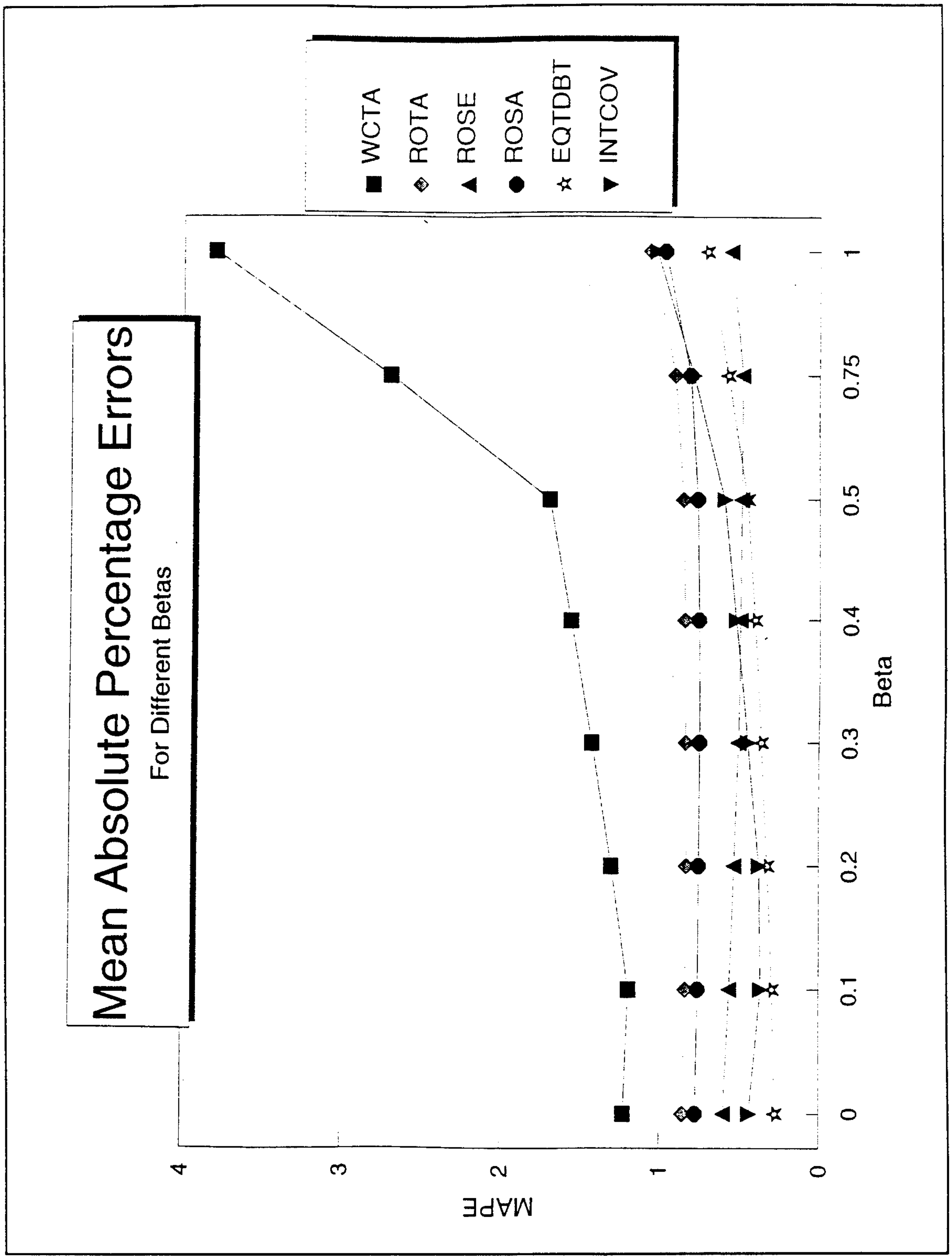

Figure 4.2 MAPEs from Industry Average Adjustment Model Forecasts for Various Betas

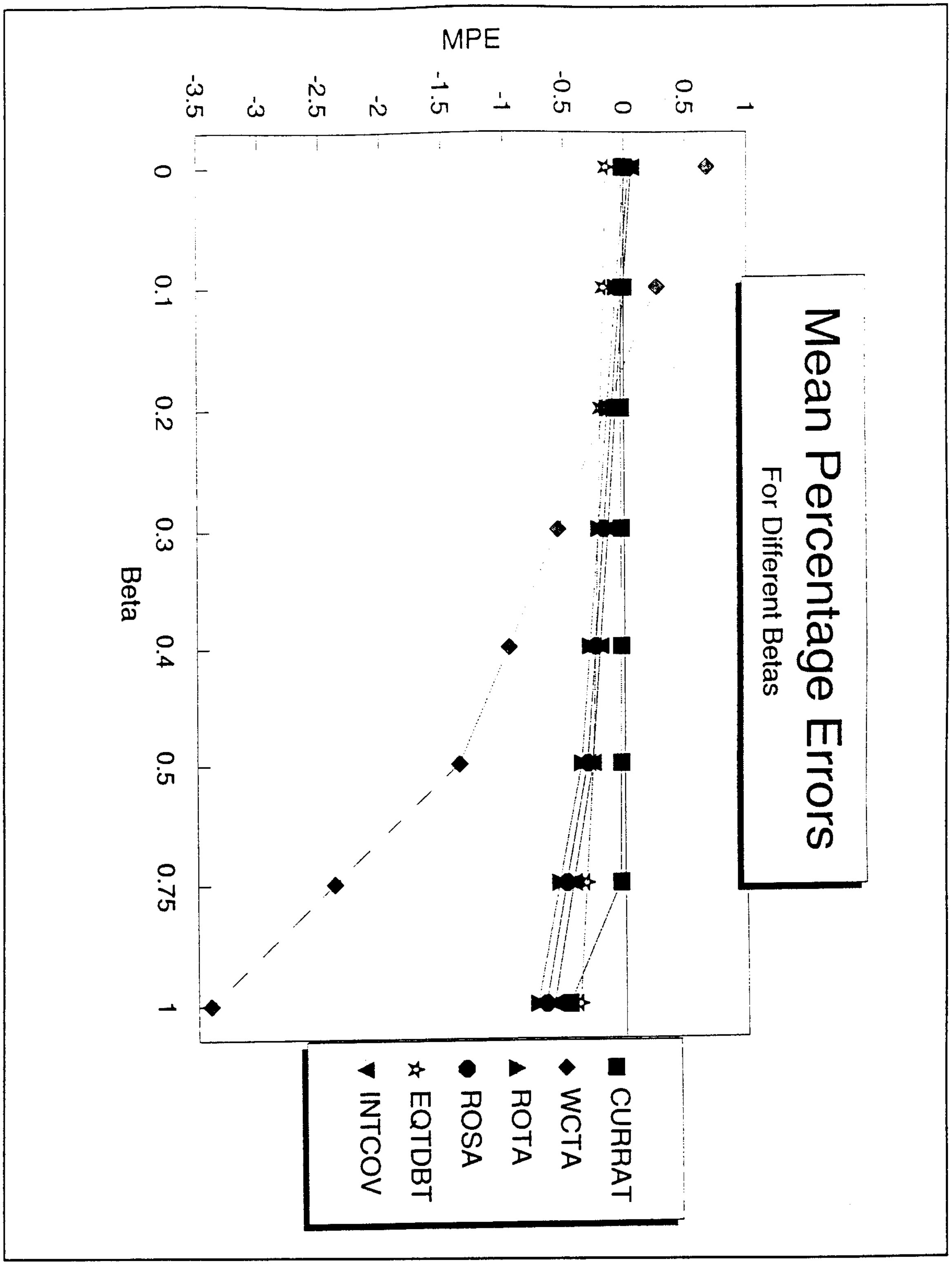

Figure 4.3 MPEs from Industry Average Adjustment Model Forecasts for Various Betas

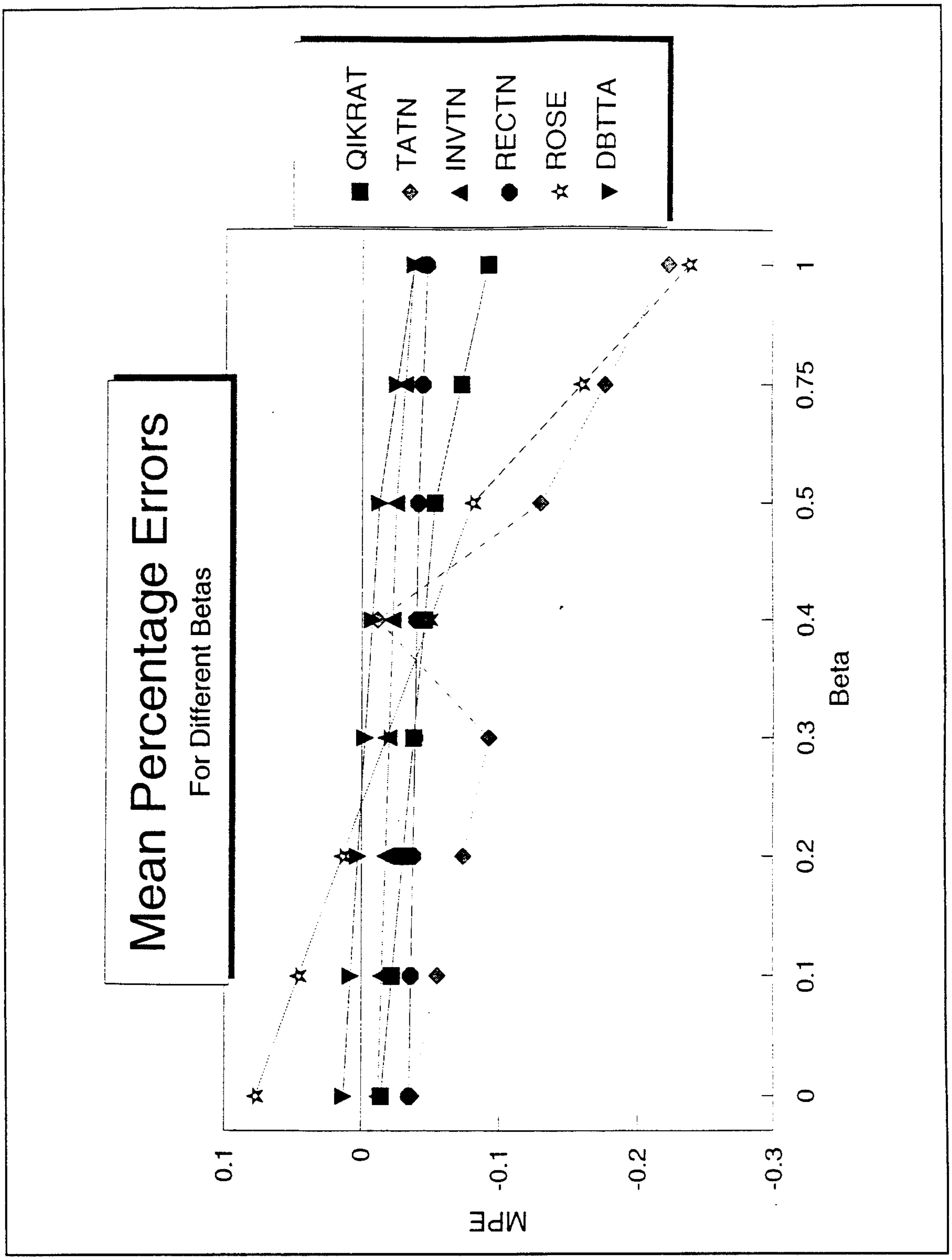

Figure 4.4 MPEs from Industry Average Adjustment Model Forecast for Various Betas

When a non-zero beta value provided the best forecasts, i.e. beta equal to .3, the errors consistently decreased as beta was varied from zero up to .2, and then increased for beta values from .3 to one. (The one exception to these consistent trends was the forecast for total asset turnover made by the industry average adjustment model.) These consistent trends in predictive ability relative to changing betas provided quantitative confidence in the model equations chosen and in the error measurement calculations.

C. MODEL BIAS AND ACCURACY

1. Introduction

The section that follows is a discussion of the analysis and results used to answer three of the thesis questions introduced in Chapter I. The questions are: (1) Which models are the most accurate?, (2) Which models are the least biased?, and (3) Is a common forecast model most useful for all ratios or does the best model depend on the ratio being forecast? The analysis focuses on comparison, for different models, of the two forecast error measures introduced in Chapter III, the accuracy error measure of Mean Absolute Percentage Error, MAPE, and the bias error measure of Mean Percentage Error, MPE.

2. Test Procedures

After a beta value of .25 was chosen for all of the partial adjustment models, forecasts were made for every ratio using all models. MAPEs and MPEs were compared ratio by ratio in order to answer the questions of model accuracy and bias for each ratio. In addition to comparing error measures, the standard deviations of the MAPEs and MPEs were checked to insure that the distribution of the errors was consistent with the choice of models gained from comparing the value of the errors. For almost every forecast, the standard deviations provided supporting evidence for the ranking of models given by the value of error measures, and never conflicted with the value of errors to the extent of contradicting the ranking of models. Detailed discussion of the standard deviations of errors for specific forecasts has therefore been omitted.

Figures 4.5 through 4.16 contain graphs illustrating the values for the MAPE and MPE for each forecasting model applied to each ratio. The graphs are organized by ratio category. Abbreviations for the models used in the legends for the graphs are as follow: random walk model, RAND WALK; simple industry average model, IAVG; industry average adjustment model, IAVG ADJ; moving average adjustment model, MA ADJ; fixed deviation adjustment model, FD ADJ; firm trend model, FIRM TREND; industry trend model, IND TREND.

The discussion below is organized as per the illustrations, in a ratio by ratio comparison of model forecasts. At the end of each ratio category, conclusions on the forecasts for ratios in that category are listed. One common standard of comparison used in the conclusion section for each ratio category is whether the more sophisticated forecasting models significantly outperformed the random walk model.

3. Liquidity Ratio Forecasts

The summary error measures for the three liquidity ratios are illustrated in Figures 4.5 through 4.7 on the following three pages.

a. *Current Ratio*

(1) Accuracy. Four models produced forecasts with accuracy errors of approximately 13 percent. The models and their forecast MAPEs were the random walk model, .1308, the fixed deviation adjustment model, .1309, the moving average adjustment model, .1316, and the industry drift model, .1326. A fifth model, the industry average adjustment model, produced forecasts with a MAPE of approximately 15 percent.

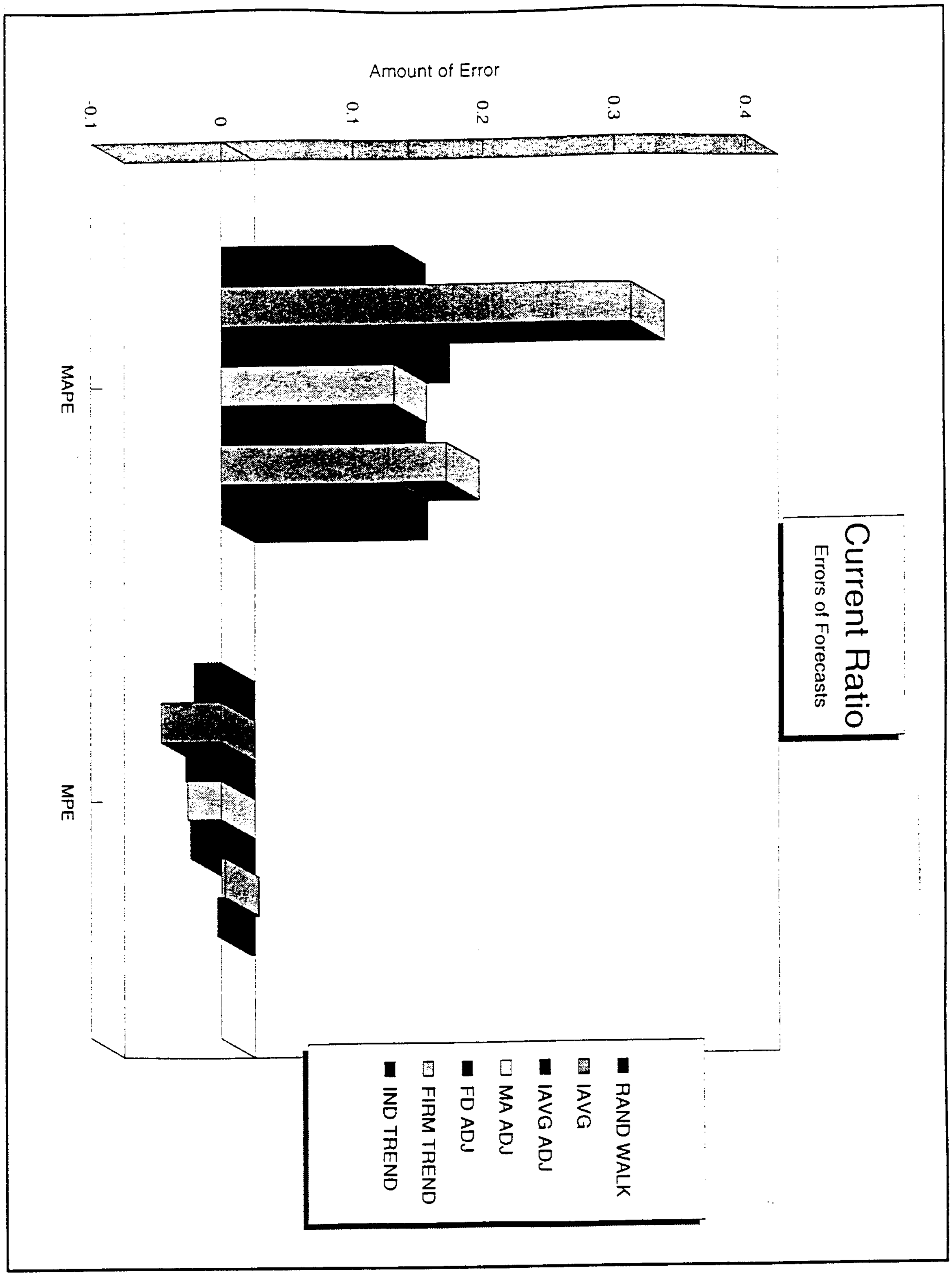

Figure 4.5 Summary Errors from Forecasts of the Current Ratio

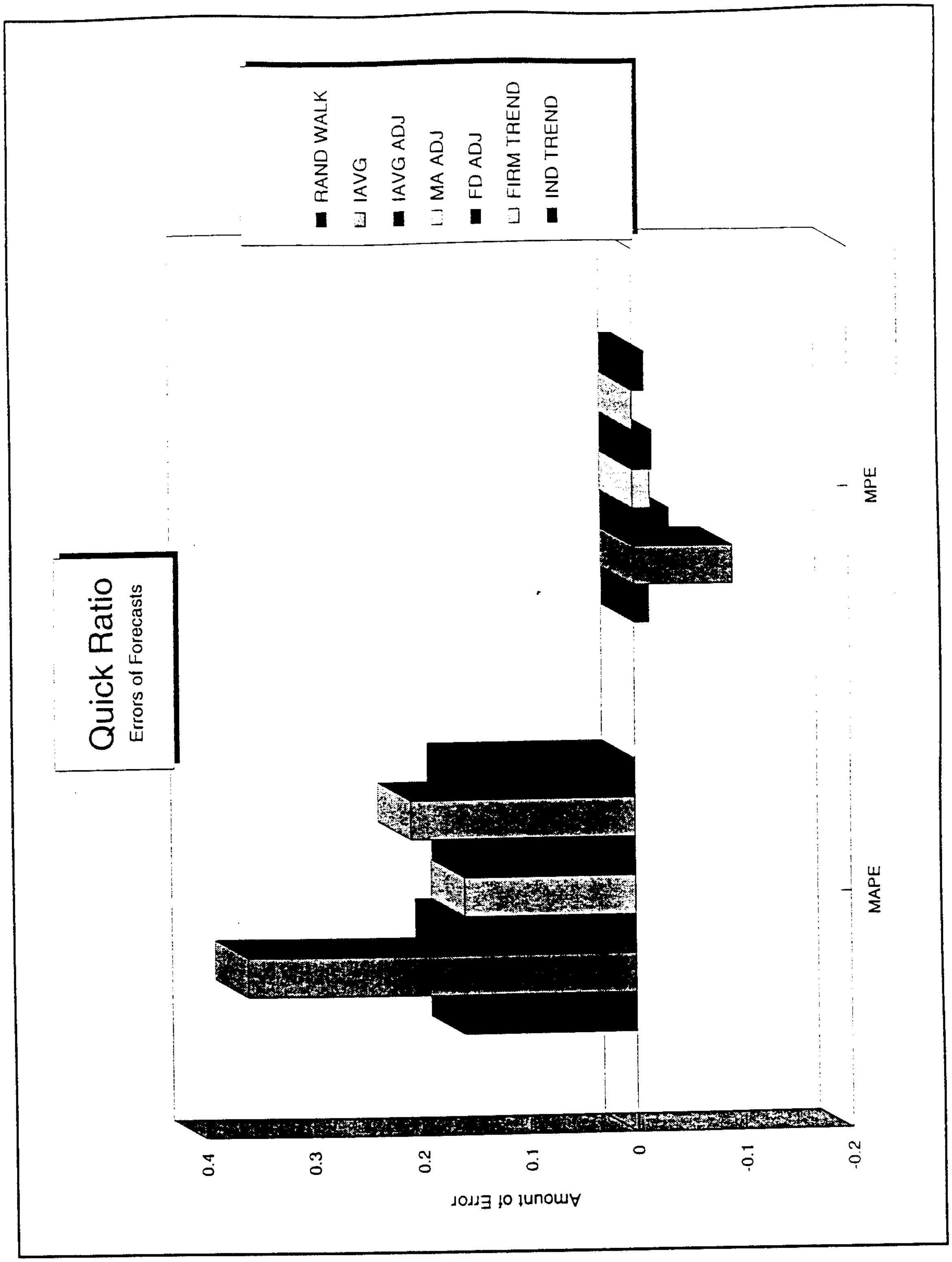

Figure 4.6 Summary Errors from Forecasts of the Quick Ratio

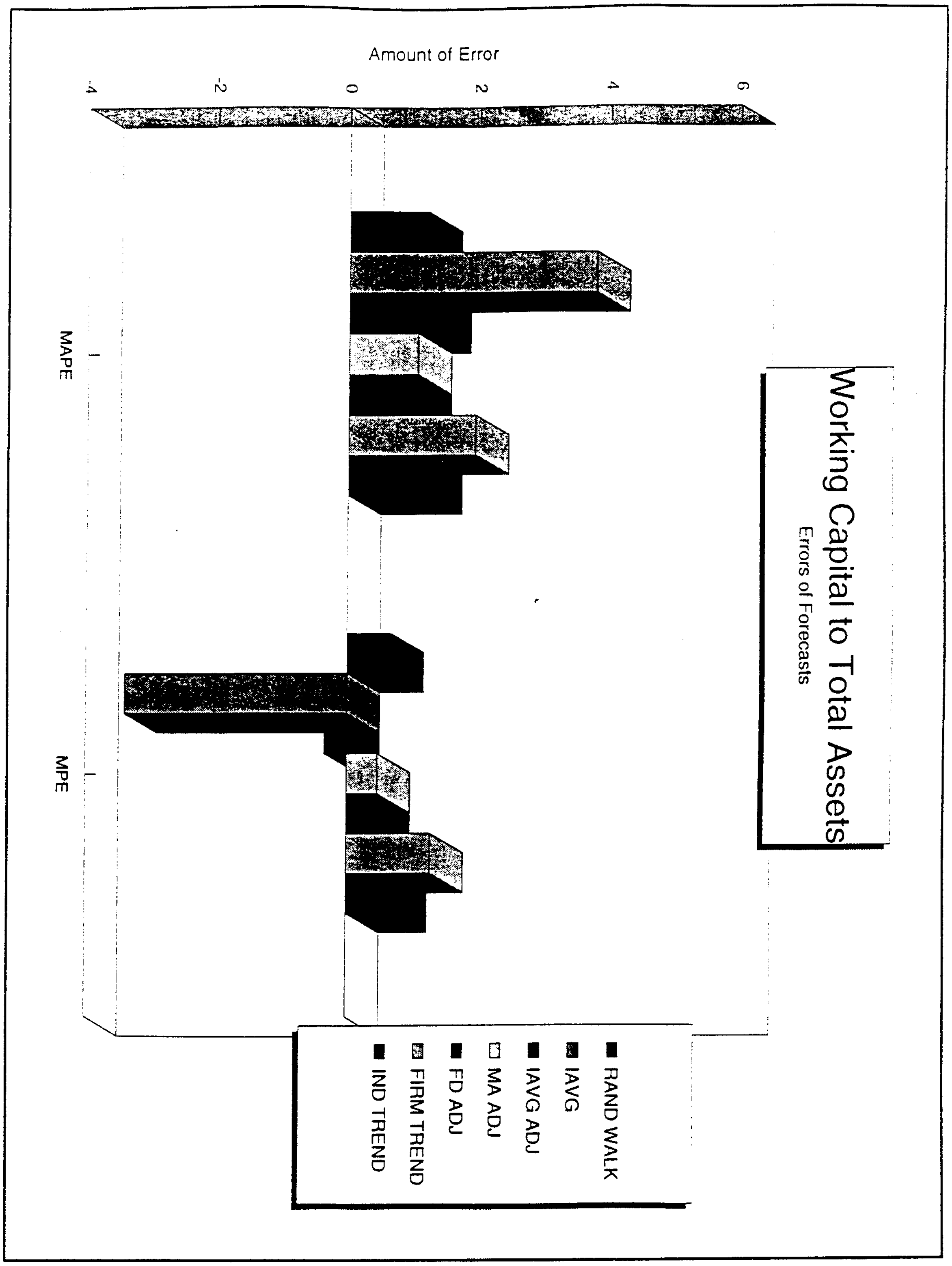

Figure 4.7 Summary Errors from Forecasts of the Working Capital to Total Assets Ratio

(2) Bias. The best forecasts in terms of minimizing bias for the current ratio were produced by the two trend models. Forecasts from these models resulted in MPEs of .0021 for the firm trend and -.0033 for the industry trend. These figures were approximately ten times less than the MPE of the next closest model. All models bias was within 3 percent of zero with the exception of the simple industry average model. Forecasts from all of the models except for the firm trend model were positively biased. (This positive bias was indicated by a negative value for MPE as explained in Chapter III.)

b. *Quick Ratio*

(1) Accuracy. The most accurate models for quick ratio forecasts were the same as for the current ratio. Forecast from the fixed deviation adjustment, moving average adjustment, random walk, and industry drift models, (listed in ascending order of error), all had approximately 16 percent accuracy error. The industry average adjustment model forecast MAPE was .1755, again within two percent of the lowest MAPE.

(2) Bias. The firm trend model again provided the decisively lowest MPE from quick ratio forecasts with a value of -.0007. The next closest models were the industry trend and random walk models which had substantially higher MPEs in the -.01 range. Forecasts for the quick ratio from all models were positively biased. All model forecast bias errors were within four percent of zero, again with the exception of the simple industry average model.

c. *Working Capital to Total Assets Ratio*

(1) Accuracy. Accuracy for forecasts of the working capital to total assets ratio were dramatically worse than for the other two liquidity ratios. The best two MAPEs were produced from the moving average and fixed deviation adjustment model forecasts but indicated approximately 108

percent error. The random walk and industry trend again were in the top four models with accuracy errors of about 124 percent.

(2) Bias. Bias results from the model forecasts for the working capital to total assets ratio were also poor. The three adjustment models produced the least bias from forecasts. The lowest was the industry average adjustment with an MPE of -.3450. The other two adjustment models had MPEs of approximately of .47. The predominate value of MPEs for the working capital to total assets was positive. Five out of the seven model forecasts had positive MPEs indicating negative bias.

(3) Additional Forecast Runs. Because the working capital to total assets ratio forecasts were so poor, two additional forecasting trials were made using the three partial adjustment models and betas of .75 and one. As noted in the first section of this chapter, the analysis to decide what beta value to choose for all models indicated that for the working capital to total assets ratio, a beta of .75 or one produced the best forecasts. These additional runs were made to test the forecasting ability of all of the partial adjustment models using higher betas.

The results from these additional forecasts were significantly different than the forecasts made using a beta of .25. The industry average adjustment model's forecasting performance was severely degraded for both errors using both higher beta values. The MPE was increased from -.3450 to -2.3829 when beta was changed from .25 to .75. The MPE increased to -3.4019 for beta equal to one. The MAPE increased from 1.3670 to 2.7012 and to 3.7995 for beta equal to .75 and one respectively.

The moving average and fixed deviation adjustment models' forecasting ability was improved for both larger beta values for both error measures. The MPE was minimized for both model forecasts with a beta of .75. The moving average forecast's MPE improved from .4755 to .0786 and the fixed deviation model's from .4748 to .0765. Both models' accuracy was best using a beta equal to one. The MAPE for the moving average model dropped from 1.0747 to .9651 and for the fixed deviation from 1.0786 to .9806. These results indicate that in order to maximize the forecasting ability of the adjustment models, beta values have to chosen on a ratio by ratio basis in addition to a model by model basis.

d. Summary of Liquidity Ratio Results

For all liquidity ratios, five models produced comparable quality forecasts, ratio by ratio. The random walk, fixed deviation adjustment, moving average adjustment, industry drift models, and industry average adjustment models produced similar forecasts for each ratio, although accuracy and bias of forecasts between ratios varied greatly.

Bias of forecasts was low for all current and quick ratio forecasts with the exception of forecasts from the simple industry average model, while bias were much greater for the working capital to total assets ratio. For all three ratios, the simple industry average model produced the worst results by far. No model significantly outperformed the random walk model.

4. Asset Management Ratio Forecasts

Figures 4.8 through 4.10 on the following three pages graph the error results for asset management ratio forecasts.

a. Total Asset Turnover Ratio

(1) Accuracy. Four models produced forecasts with MAPES of approximately .12. These models and MAPEs were the random walk, .1190, the industry trend, .1200, the moving average adjustment, .1218, and the fixed deviation adjustment, .1221.

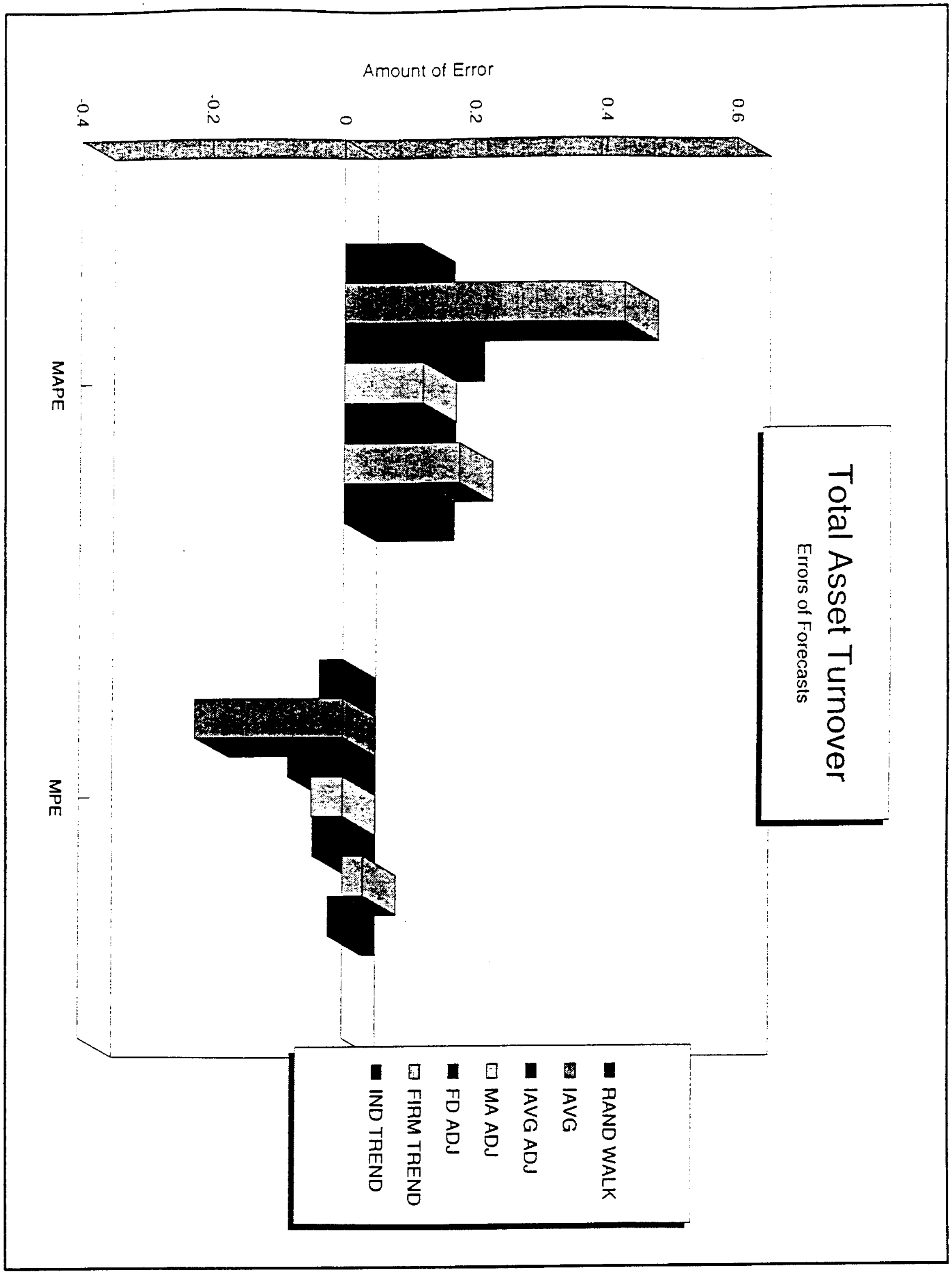

Figure 4.8 Summary Errors from Forecasts of the Total Asset Turnover Ratio

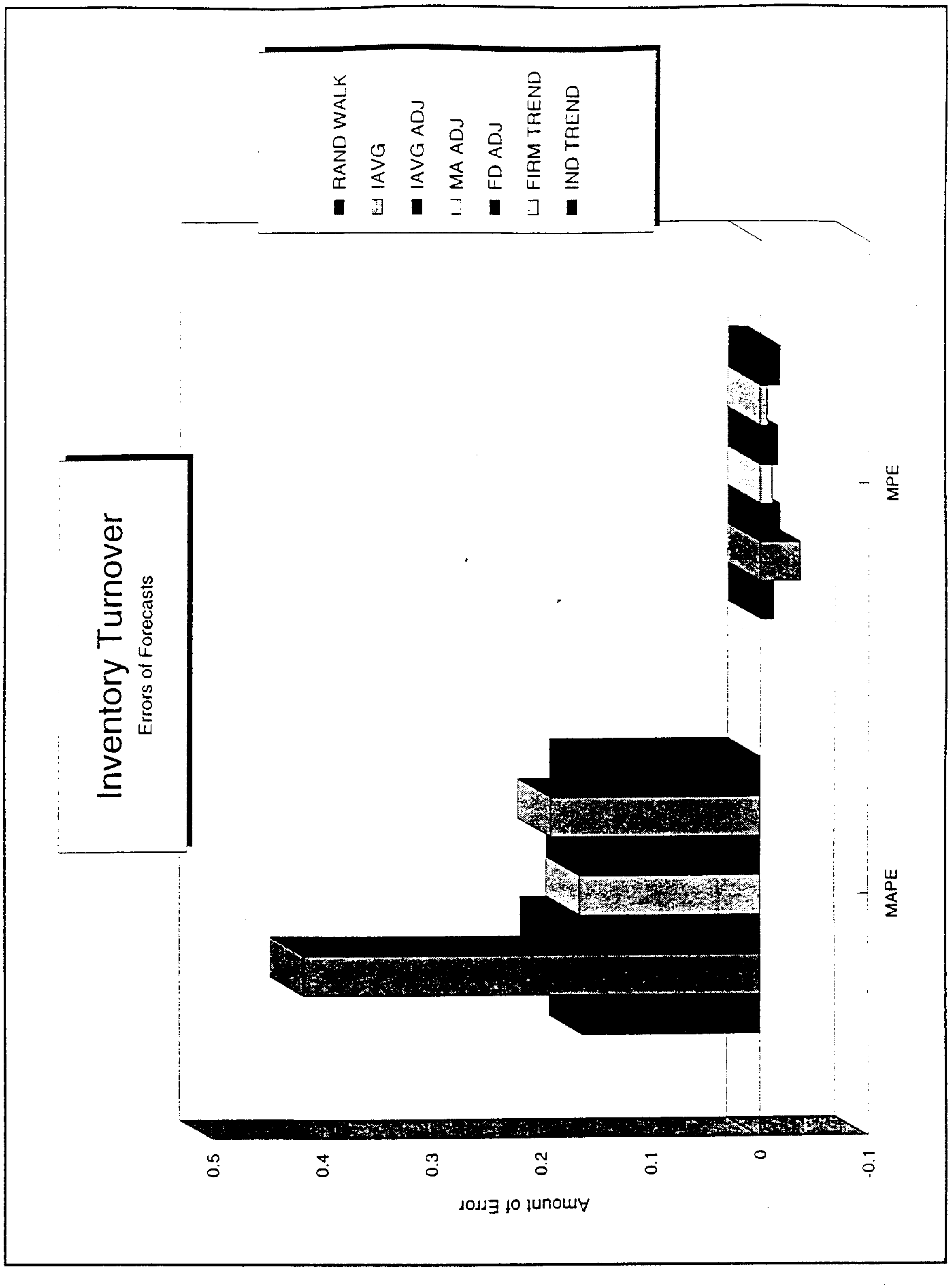

Figure 4.9 Summary Errors from Forecasts of the Inventory Turnover Ratio

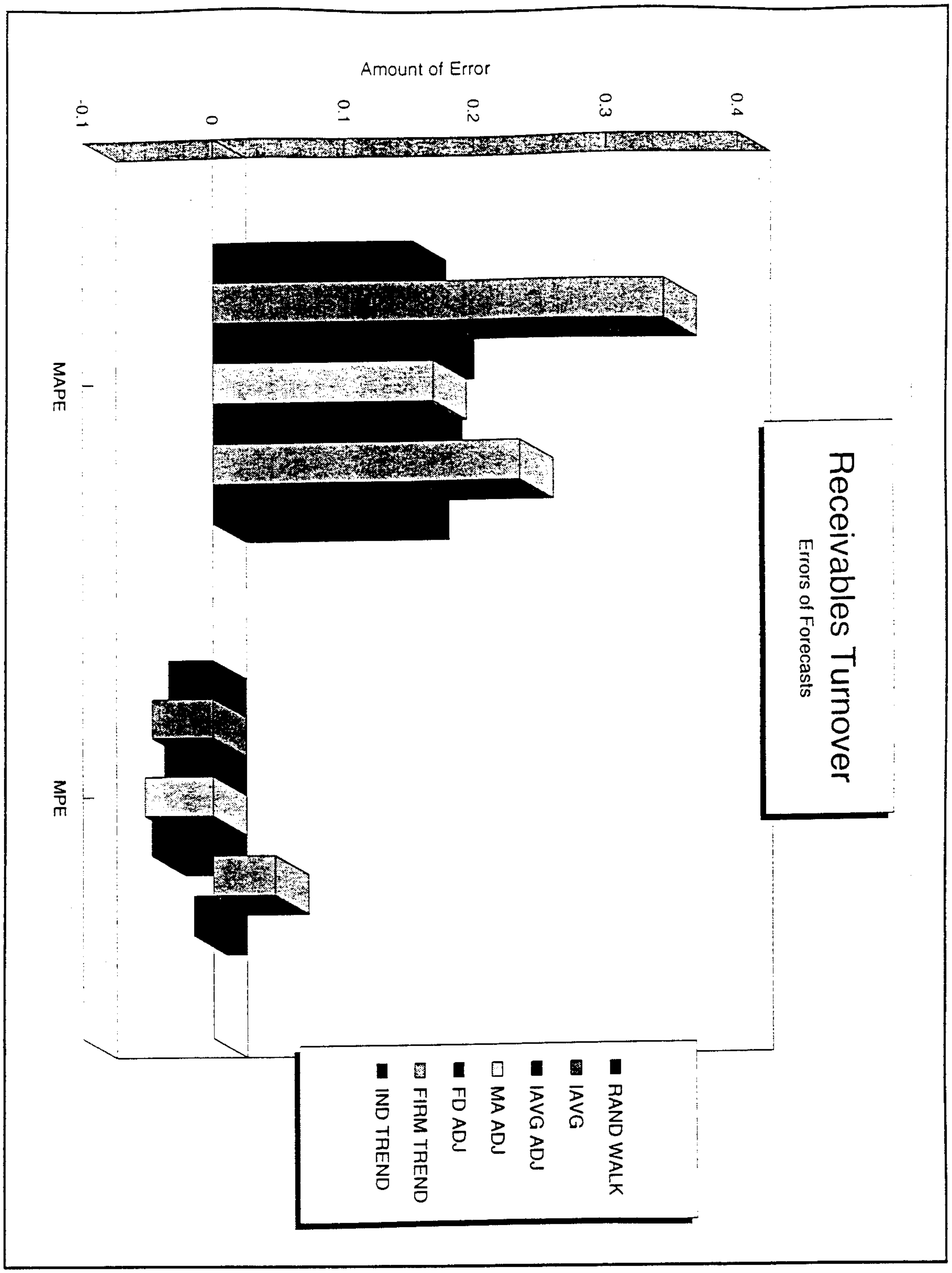

Figure 4.10 Summary Errors from Forecasts of the Receivables Turnover Ratio

(2) Bias. Five models produced forecasts with bias errors within five percent of zero. The two trend models, industry and firm, had the best MPEs, -.0222 and .0316 respectively. The random walk, and the fixed deviation and moving average adjustment models followed. Bias was positive for all models except for the firm trend model.

b. Inventory Turnover Ratio

(1) Accuracy. The four most accurate models for the total asset turnover ratio forecasts were most accurate for the inventory turnover ratio as well. The industry trend, random walk, moving average adjustment, and fixed deviation adjustment, all produced forecasts with accuracy errors of about 16 percent.

(2) Bias. All models produced forecasts with bias errors within four percent of zero. The firm trend model's MPE of -.0068 was about half the value of the next two low values, .0114 for the moving average adjustment model, and .0119 for the random walk. All models produced forecasts with positive bias.

c. Receivables Turnover Ratio

(1) Accuracy. Five models produced forecasts with accuracy errors of between 15 and 17 percent for the receivables turnover ratio. Forecasts from the random walk model, industry trend model, and fixed deviation adjustment model produced the lowest MAPEs, .1534, .1554, and .1654 respectively.

(2) Bias. The industry trend model forecasts for receivables turnover resulted in a MPE of -.0153 which was approximately half of the value of the next least biased models. All other models produced forecast with bias errors of within three to five percent of zero. The forecasts indicated that all models were positively biased with the exception of the firm trend model.

d. Summary of Asset Management Results

For each asset management ratio, the random walk model, industry trend model, moving average adjustment model, and fixed deviation adjustment model all produced forecasts with comparable errors. These models' forecasts were on average accurate within 18 percent. Their forecasts all had bias errors of within five percent of zero. The simple industry average model again consistently produced the worst forecasts. No model significantly outperformed the random walk model.

5. Profitability Ratio Forecasts

The accuracy of forecasts for profitability ratios from all models were decidedly worse than for any other ratio category. None of the models produced forecasts for the three ratios with less than 50 percent accuracy error. Bias for the forecasts as indicated by MPE, however, was relatively low for the best models for all ratios. Figures 4.11 through 4.13 on the following three pages summarize the errors for each profitability ratio from all forecasts.

a. Return on Total Assets Ratio

(1) Accuracy. Accuracy errors for forecasts of the return on total assets ratio ranged from approximately 83 to 112 percent. The four models which produced the most accurate forecasts and their MAPEs were the industry average adjustment, .8357, the random walk, .8537, the moving average adjustment, .8539, and the fixed deviation adjustment, .8680.

(2) Bias. For the return on total assets ratio, the random walk models' forecasts had the lowest bias by far with an MPE of .0099. The next two least biased models and their MPEs were the moving average adjustment, .0716, and the fixed deviation adjustment, .1105. Five models had negative bias and two, the simple industry average and the industry average adjustment, had positive bias.

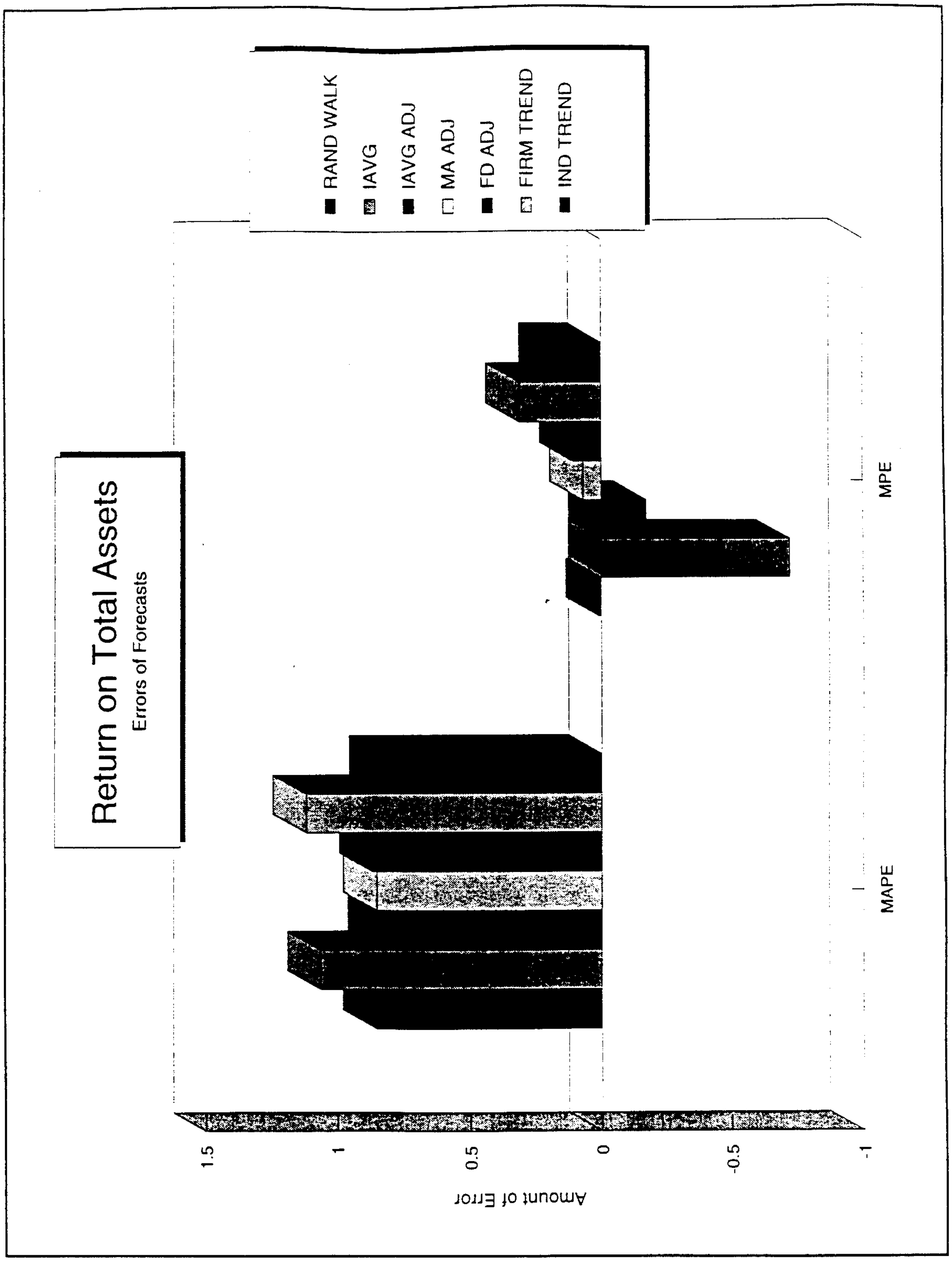

Figure 4.11 Summary Errors from Forecasts of the Return on Total Assets Ratio

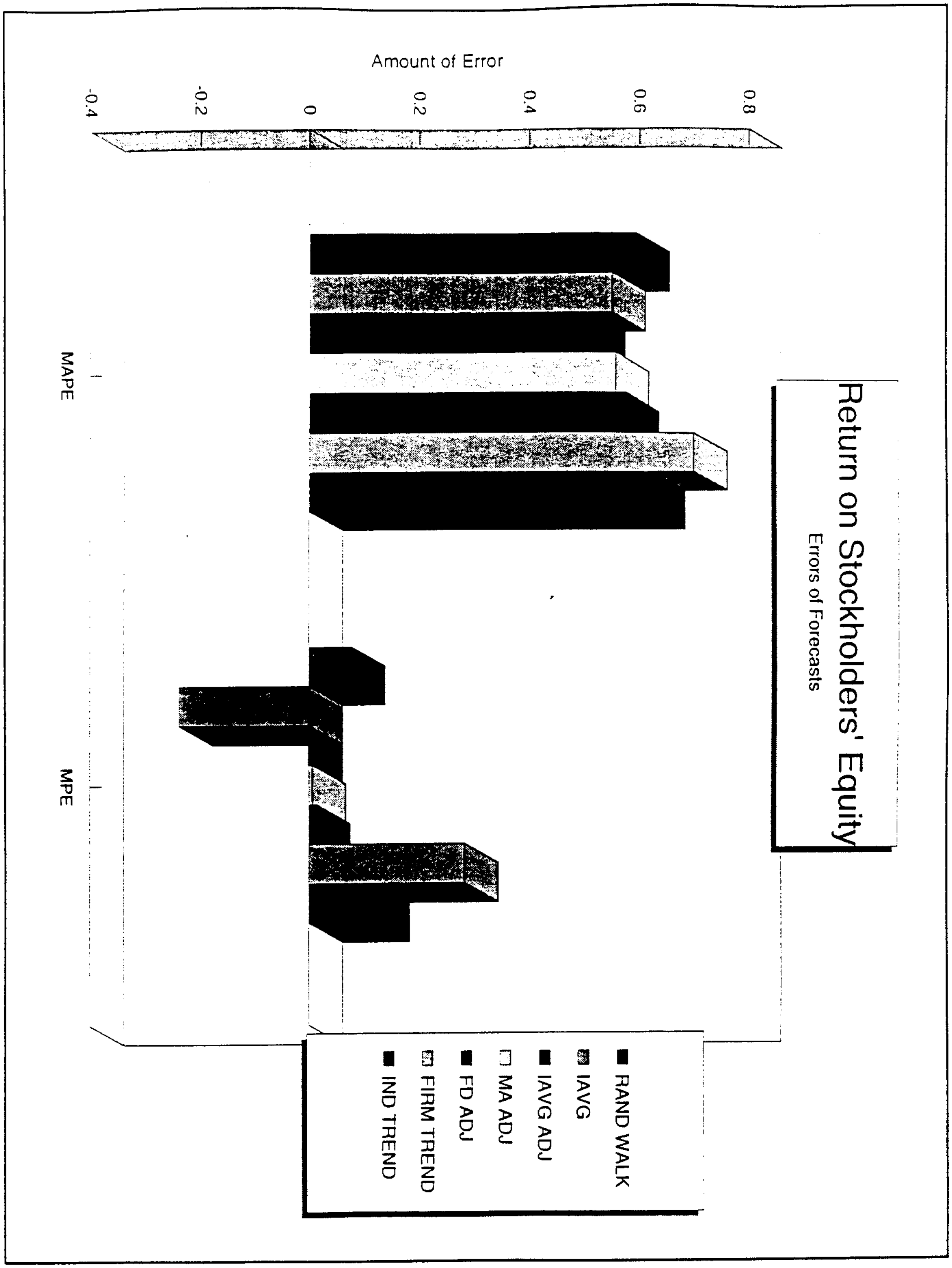

Figure 4.12 Summary Errors from Forecasts of the Return on Stockholder's Equity Ratio

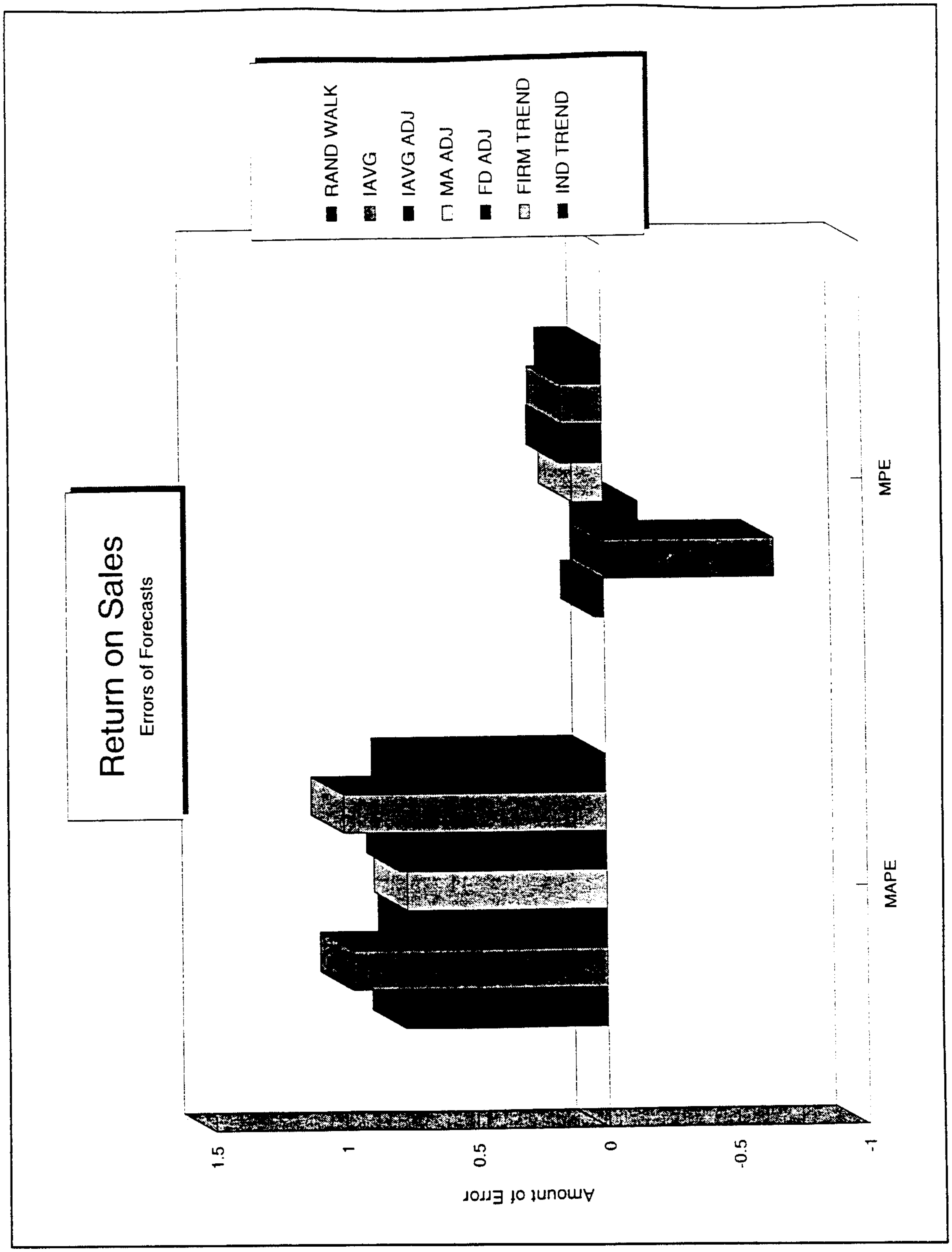

Figure 4.13 Summary Errors from Forecasts of the Return on Sales Ratio

b. Return on Stockholders' Equity Ratio

(1) Accuracy. All models produced forecasts for return on stockholders' equity with accuracy errors between 50 and 75 percent, the most accurate of all the profitability ratios. The four models producing the lowest MAPEs were the industry average adjustment, .5139, the simple industry average, .5515, the moving average adjustment, .5587, and the fixed deviation adjustment, .5779.

(2) Bias. The bias figures for three model forecasts were below two percent. These models and their MPEs were the industry average adjustment, -.0018, the moving average adjustment, .0063, and the fixed deviation adjustment, .0133. Bias from five models were negative, and two positive. The only models forecasting with positive bias were again the simple industry average and industry average adjustment.

c. Return on Sales Ratio

(1) Accuracy. Accuracy errors of forecasts for the return on sales ratio ranged from about 75 to 100 percent. The top four models and MAPEs were the industry average adjustment, .7499, the moving average adjustment, .7641, the industry trend, .7709, and the random walk, .7727.

(2) Bias. The random walk produced the lowest MPE of .0392, followed by the moving average adjustment model with an MPE of .1185, and the firm trend model with an MPE of .1293. The simple industry average and industry average adjustment models were again the only models to produce forecasts with positive bias.

d. Summary of Profitability Ratio Results

The overriding conclusion to be drawn from these results is that all models demonstrated poor forecasting ability for all profitability ratios in terms of accuracy. The simple industry average model did not stand out as having the worst forecasting ability, probably because forecasts from all models were so bad. No model significantly outperformed the random walk, although the industry average adjustment model did consistently rank above the random walk model in terms of accuracy error by a small margin.

6. Leverage Ratio Forecasts

The results of the error measures for forecasts of the leverage ratios are illustrated in the graphs in Figures 4.14 through 4.17 on the following three pages.

a. Equity to Total Liabilities Ratio

(1) Accuracy. Four models forecasts' yielded MAPEs of between 27 and 30 percent for the equity to debt ratio. The models and MAPEs were the random walk, .2726, the fixed deviation adjustment, .2826, the moving average adjustment, .2895, and the industry trend, .2960.

(2) Bias. The MPEs for the equity to debt ratio varied significantly but were negative for all models. The firm trend and industry trend models provided forecasts with three time less bias then the next best model, -.0200 and -.1460 respectively. The random walk provided the next closest MPE of -.1460.

b. Debt to Total Assets Ratio

(1) Accuracy. Accuracy errors for the forecasts of the debt to total assets ratio by the random walk model, the moving average adjustment model, the fixed deviation adjustment model, and the industry trend model were all approximately eight percent. These were the same four models that produced the most accurate forecasts for the equity to debt ratio.

(2) Bias. All model forecasts had MPEs within four percent of zero. The firm trend model forecasts had a significantly lower MPE of .0002 than did the other models. The fixed deviation model and firm trend model had the next lowest MPEs of .0120 and -.0124 respectively. Four of the model MPEs indicated negative bias and three indicated positive bias.

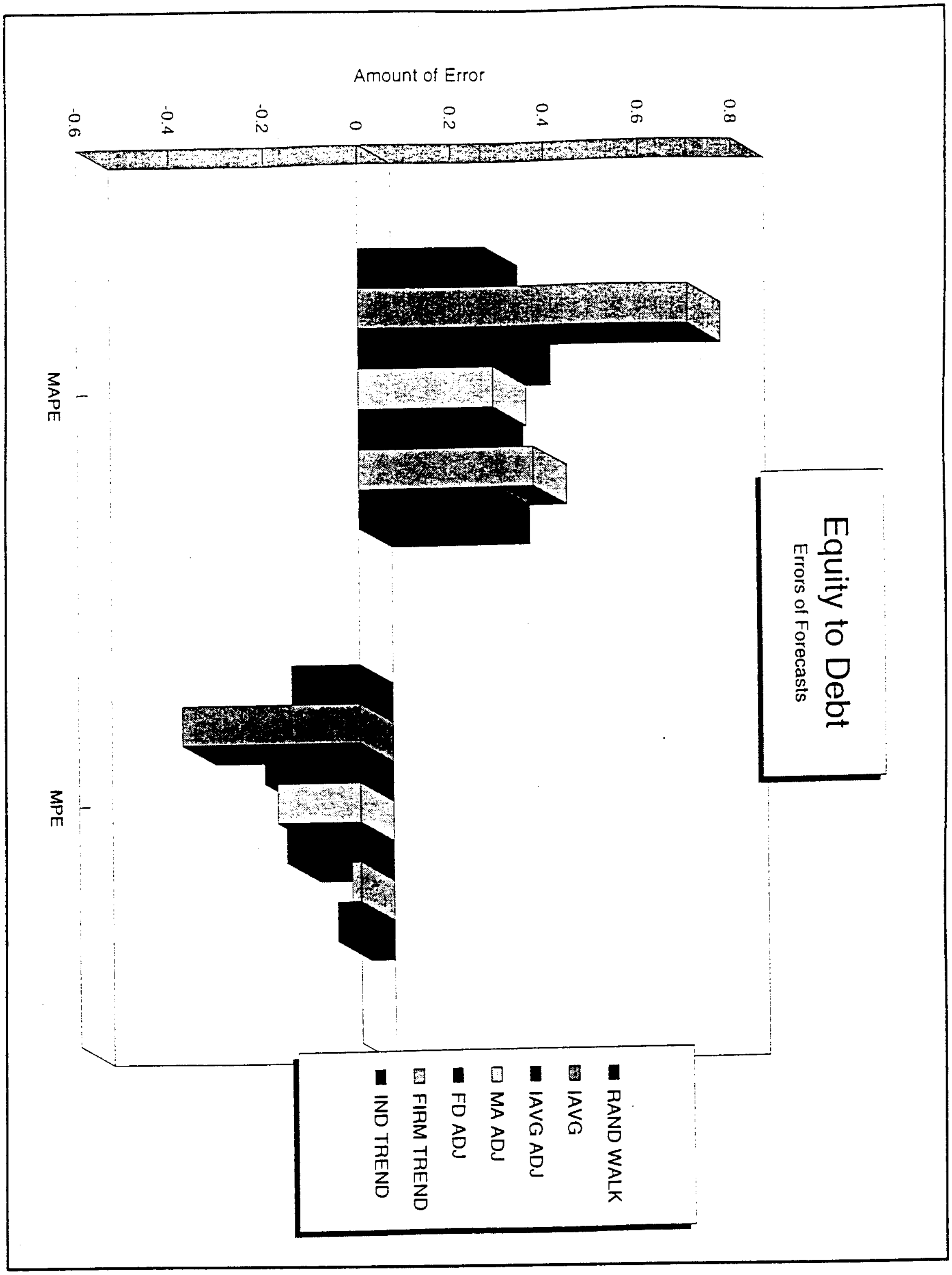

Figure 4.14 Summary Errors from Forecasts of the Equity to Debt Ratio

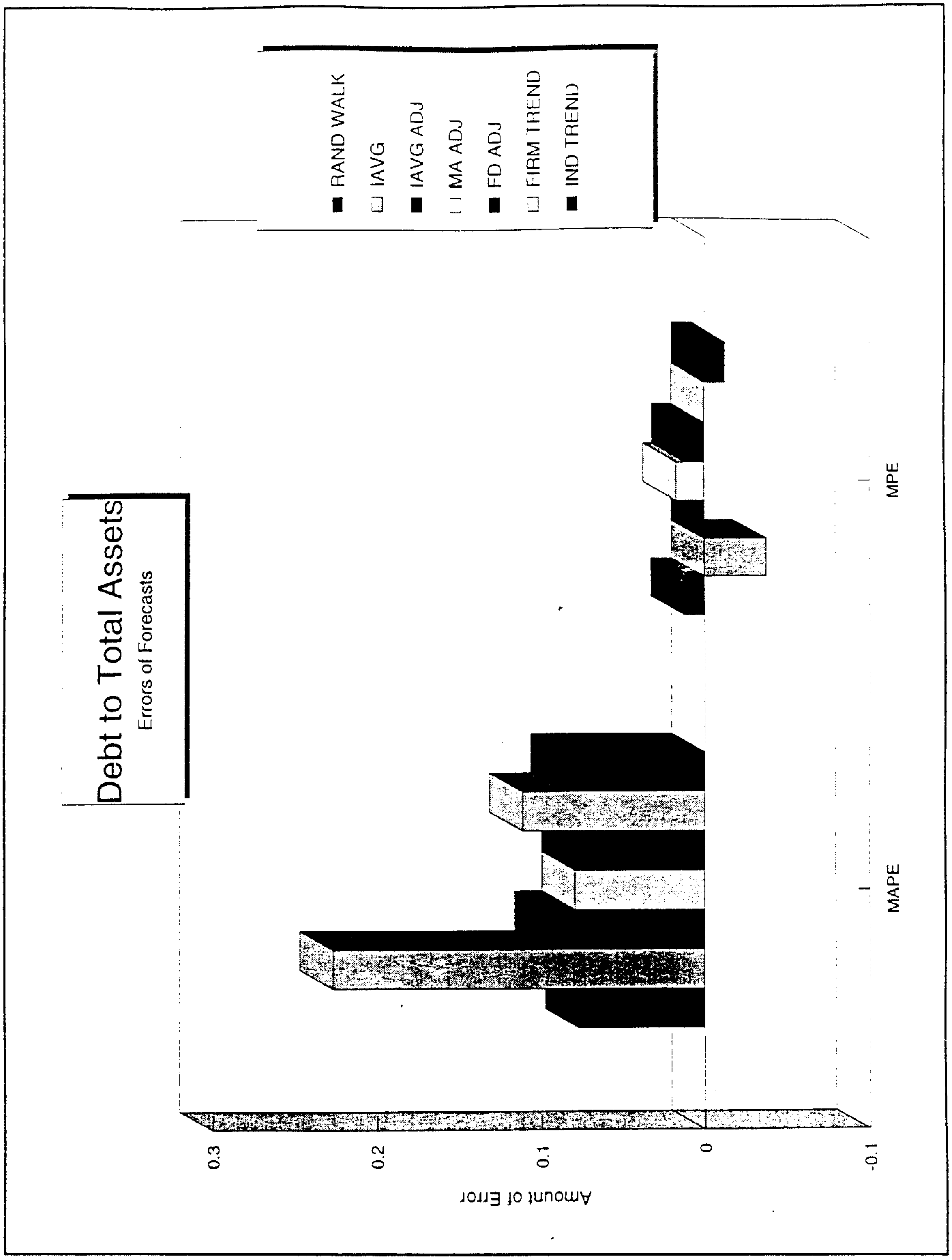

Figure 4.15 Summary Errors from Forecasts of the Debt to Total Assets Ratio

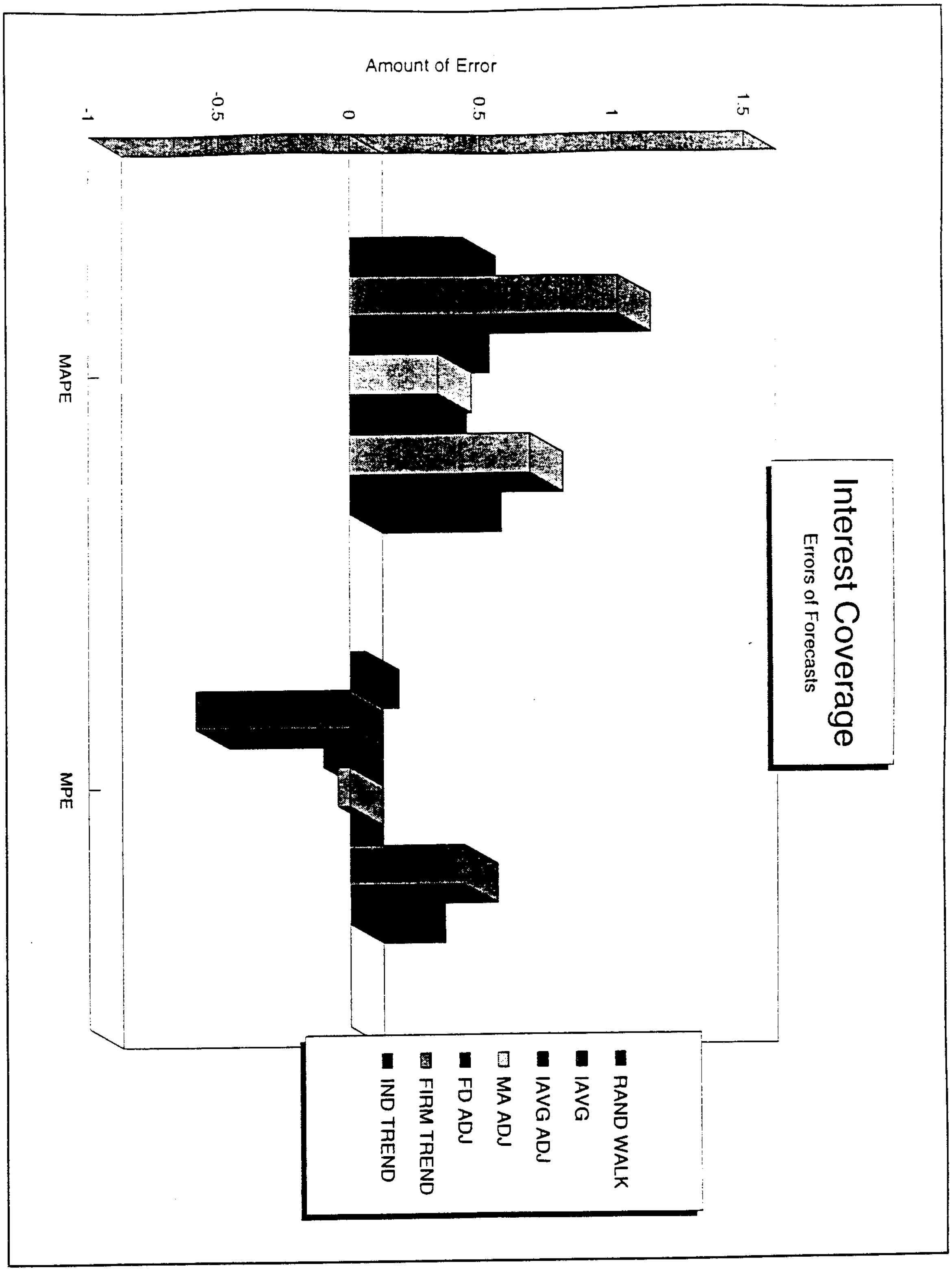

Figure 4.16 Summary Errors from Forecasts of the Interest Coverage Ratio

c. *Interest Coverage Ratio*

(1) Accuracy. No models produced forecasts for the interest coverage ratio with accuracy errors of less than 30 percent, but five models produced forecasts with errors less than 50 percent. The fixed deviation adjustment model had the lowest MAPE of .3232, followed by the moving average adjustment MAPE of .3413, and the industry average adjustment MAPE of .4097.

(2) Bias. The fixed deviation adjustment model forecasts provided by far the lowest MPE of -.0013. It was followed by the moving average adjustment MPE of -.0462, and the random walk MPE of .0614. Four MPEs were positive and three were negative.

d. *Summary of Leverage Ratio Results*

For the leverage ratios, forecasting performance of models varied widely in terms of both accuracy and bias from ratio to ratio. The debt to total assets was forecast comparably well by four models. Forecasts for the equity to debt and interest coverage ratios were relatively poor. The simple industry average model made the consistently worst forecasts. No model consistently outperformed the random walk model.

7. Summary of Bias and Accuracy Results

Table 4.4 contains a summary of the results of the accuracy and bias analysis. The best model in terms of bias error, accuracy error, and both errors, is listed for each ratio. The procedure for choosing the best model in terms of both errors was developed based on the premise that accuracy was more important than bias in determining the quality of forecasts. The MAPE value was thus used first to choose the most accurate models. The MPEs were then checked to confirm the choice of this model as best, or to break ties between models with equal forecasting accuracy. As long as the most accurate model had an MPE that was relatively comparable to the MPE of other top models, it was chosen as the best at forecasting overall.

Also listed is the value of the third lowest error measure value which is listed as "Range" in the table. This third lowest error value is included to indicate the degree that the best model forecasts differed from other models which ranked in the top three for that ratio. This range figure helps to illustrate how predictable a specific ratio was overall and how significantly the top models differed in forecasting ability.

D. CHOOSING THE "BEST" MODELS

1. Which Models Are Most Accurate?

The accuracy errors provide a muddled picture of model forecasting ability. The random walk model was the consistently most accurate forecaster for the ratios overall, with the lowest MAPE for five of the 12 ratios. For the liquidity ratios, in addition to the random walk, the fixed deviation adjustment, moving average adjustment, industry drift, and industry average models all performed relatively well. For the asset management ratios the industry trend model, the moving average adjustment model, the fixed deviation adjustment model as well as the random walk model all provided comparably accurate forecasts. For the profitability ratio category, the industry average adjustment model was most accurate but still did not outperform the random walk by a significant amount for two of the three ratios. For the leverage ratios, the random walk model was again the most accurate, followed by the moving average and fixed deviation adjustment models. The least convoluted general observation which can be made on the results of this accuracy analysis is that the none of the more sophisticated models is able to outperform the random walk across all ratio categories.

Ratio	1.Most Accurate Model 2.MAPE 3.Range (3rd Lowest MAPE)	1.Least Biased Model 2.MPE 3.Range (3rd Lowest MPE)	1.Model Best Overall 2.MPE 3.MAPE
Current	1.Random Walk 2.MAPE .1308 3.Range .1315	1.Firm Trend 2.MPE -.0030 3.Range -.0212	1.Random Walk 2.MPE -.0212 3.MAPE .1308
Quick	1.Fixed Dev Adj 2.MAPE .1597 3.Range .1609	1.Firm Trend 2.MPE -.0007 3.Range -.0140	1.Fixed Dev Adj 2.MPE -.0183 3.MAPE .1597
WorkCap to Tot Assets	1.Mov Avg Adj 2.MAPE 1.0747 3.Range 1.2261	1.Ind Avg Adj 2.MPE -.3450 3.Range .4755	1.Mov Avg Adj 2.MPE .4755 3.MAPE 1.0747
Total Asset Trnover	1.Random Walk 2.MAPE .1190 3.Range .1218	1.Ind Trend 2.MPE -.0222 3.Range -.0363	1.Random Walk 2.MPE -.0363 3.MAPE .1190
Invntry Trnover	1.Ind Trend 2.MAPE .1622 3.Range .1648	1.Firm Trend 2.MPE -.0068 3.Range -.0119	1.Ind Trend 2.MPE -.0179 3.MAPE .1622
Recvble Trnover	1.Random Walk 2.MAPE .1534 3.Range .1655	1.Ind Trend 2.MPE -.0153 3.Range -.0377	1.Random Walk 2.MPE -.0345 3.MAPE .1534
Rtrn on Total Assets	1.Ind Avg Adj 2.MAPE .8357 3.Range .8539	1.Random Walk 2.MPE .0099 3.Range .1105	1.Random Walk 2.MPE .0099 3.MAPE .8537
Rtrn on Stkhldr Equity	1.Ind Avg Adj 2.MAPE .5139 3.Range .5587	1.Ind Avg Adj 2.MPE -.0018 3.Range .0133	1.Ind Avg Adj 2.MPE -.0018 3.MAPE .5139
Rtrn on Sales	1.Ind Avg Adj 2.MAPE .7499 3.Range .7709	1.Random Walk 2.MPE .0392 3.Range .1293	1.Ind Avg Adj 2.MPE -.1351 3.MAPE .7499
Equity to Debt	1.Random Walk 2.MAPE .2726 3.Range .2860	1.Firm Trend 2.MPE -.0200 3.Range -.1460	1.Random Walk 2.MPE -.1460 3.MAPE .2726
Debt to Total Assets	1.Random Walk 2.MAPE .0779 3.Range .0802	1.Firm Trend 2.MPE .0002 3.Range .0129	1.Random Walk 2.MPE .0129 3.MAPE .0779
Intrst Covrage	1.Fixed Dev Adj 2.MAPE .3233 3.Range .4097	1.Fixed Dev Adj 2.MPE -.0013 3.Range .0614	1.Fixed Dev Adj 2.MPE -.0013 3.MAPE .3233

Table 4.4 Models Whose Forecasts Produced the Lowest Summary Error Measures

a. *Which Model Forecasts Were Least Biased?*

The chart results illustrate that in terms of minimizing bias, the trend models were marginally superior. The trend models were least biased in seven out of 12 ratio forecasts, and for three out of the four ratio categories. The firm trend model's forecasts minimized the MPE for five out of the 12 ratios. The trend models' bias errors were best relative to those of other models for the ratios that were most accurately forecast. For the ratios which were least accurately forecast, the profitability ratios, the working capital to total assets ratio, and the interest coverage ratio, the trend model forecasts had relatively more bias compared to other models.

b. *Which Model Forecasts Were Best Overall?*

The best model in terms of minimizing errors for both bias and accuracy over all ratio forecasts was the random walk model. The random walk ranked best for six out of 12 ratios forecast. No other model ranked best for more than two ratios.

c. *Does the Best Model Depend on the Ratio Being Forecast?*

The above summary of results from this analysis indicates that in terms of both accuracy and bias, the best model depends, in part, on the ratio category being forecast.

d. *What Are Plausible Forecasting Models?*

All models included in this study performed well for some ratios, with the exception of the simple industry average model. The simple industry average model performed poorly across all ratio categories for both error measures. It is the only model which could be designated as an implausible forecasting model. For all ratio categories except for the profitability ratios, the simple industry average model was distinctly worst in forecasting ability. For the profitability ratios its forecasts were still relatively poor, although its performance did not differ as dramatically from the other models for this category.

E. FORECASTING ABILITY IN PERIODS OF GROWTH AND DECLINE

1. Background

In order to answer the thesis questions on model forecasts in periods of growth and decline, the forecast errors for the years 1987 and 1988 were aggregated and compared to the aggregated errors of forecasts from the years 1991 and 1992. Research into the condition of defense spending over these two periods reveals that the two year segments do represent distinctly different conditions of the financial health of the industry.

The U.S. defense spending increases of the 1980's actually peaked in 1985 and then slowly declined through 1990 when they began a dramatic decline. The figures contained in the annual publication *National Defense Budget Estimates for FY 1994*, from the Office of the Comptroller, Department of Defense [Ref 7] show that, although not technically growth years, 1987 and 1988 represent robust years for defense companies. Defense spending in general for these two years was high relative to historical spending figures. Because the firms for inclusion in this thesis's data base were selected from the top 100 defense contractors, defense procurement constant dollar budget authority represents a particularly useful method to determine the relative strength of the defense industry for this thesis.

The procurement constant dollar budget authority figures indicate that procurement for 1987 and 1988 was, with the exception of the unprecedented years of 1983 through 1986, at its highest level since 1968. In constant 1994 dollars, procurement spending for the years 1971 through 1980 was below 61 billion annually. Procurement budget authority for 1987 and 1988 was 98 billion and 94 billion respectively. [Ref 7]

Relative to historical figures, the high 1987 and 1988 procurement spending made these healthy years for the companies from which the thesis data was drawn.

By 1991 the procurement spending had dropped off approximately 23 percent to 77 billion constant 1994 dollars. In 1992, the procurement budget authority continued its decline to 66 billion dollars. [Ref 7] In contrast to the earlier period, 1991 and 1992 represented a period of significant contraction for defense procurement spending.

The two periods 1987 to 1988, and 1991 to 1992, although not providing the desired contrast of growth and decline, at least can be used to compare a period of health for the defense industry, with one of decline. In the text which follows and on graphs which illustrate the results of the comparison of forecasts between these two periods, the use of the terms growth and decline was used for the sake of simplicity.

2. Analysis and Results

The forecasts for 1987 and 1988 were used to produce a MAPE and MPE for each model for each ratio for this growth period. Similarly, MAPEs and MPEs were calculated from the forecasts for 1991 and 1992. These error measures were then compared model by model to determine if the forecasting ability was affected by the health of the industry.

The graphs in Figures 4.17 through 4.20 on the following four pages illustrate the comparison between some of the better performing forecasting models for the whole period. Their forecasts for the period 1987 through 1992 is compared to forecasts for the periods 1987 through 1988, and 1991 through 1992. Included are the random walk MAPE and MPE, the industry trend MAPE, and the firm trend MPE. The graphs indicate that no model forecasts were consistently better or worse in one of the two periods. The lack of consistently

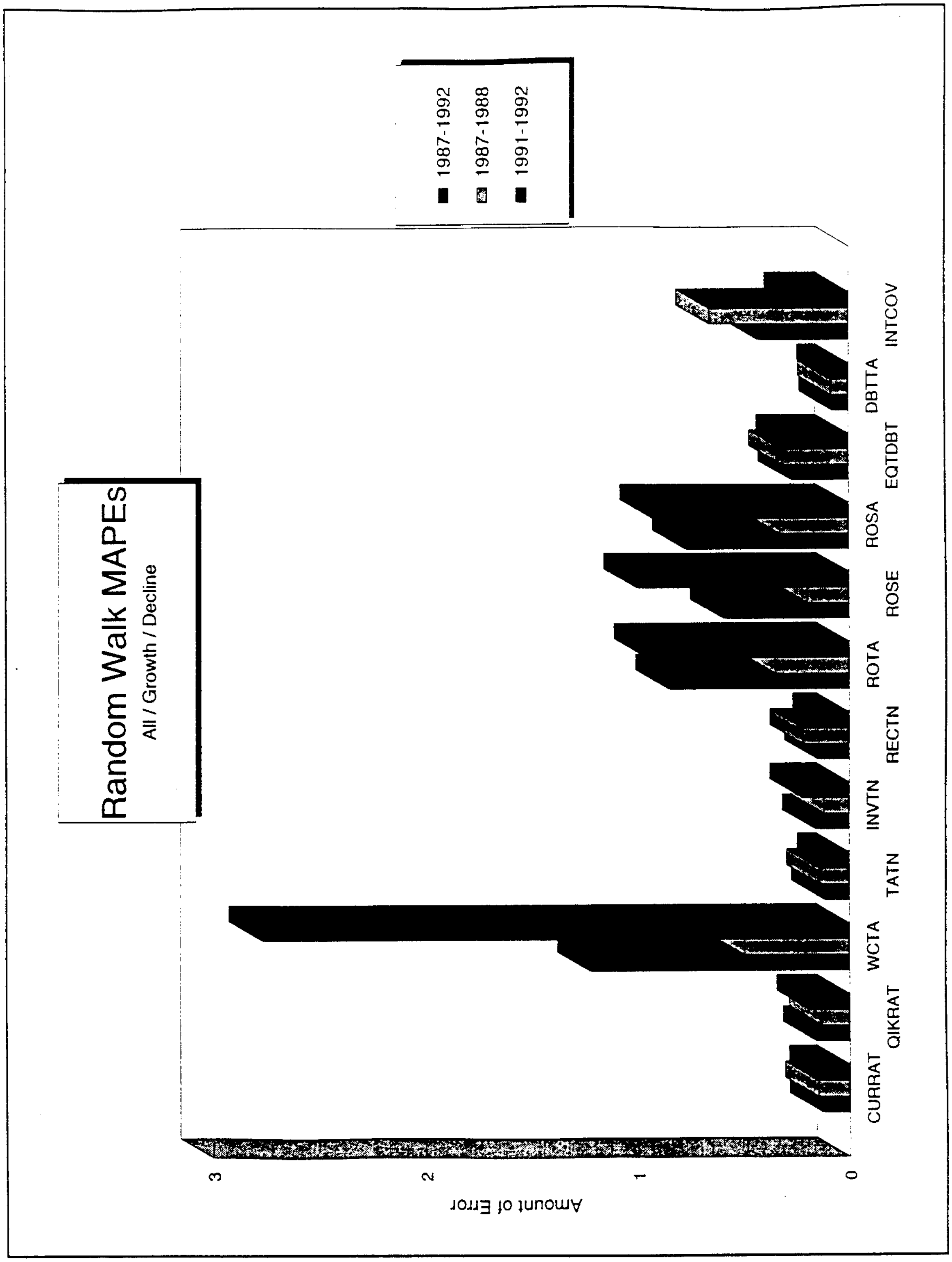

Figure 4.17 Comparison of Random Walk Forecast MAPE in Periods of Industry Growth and Decline

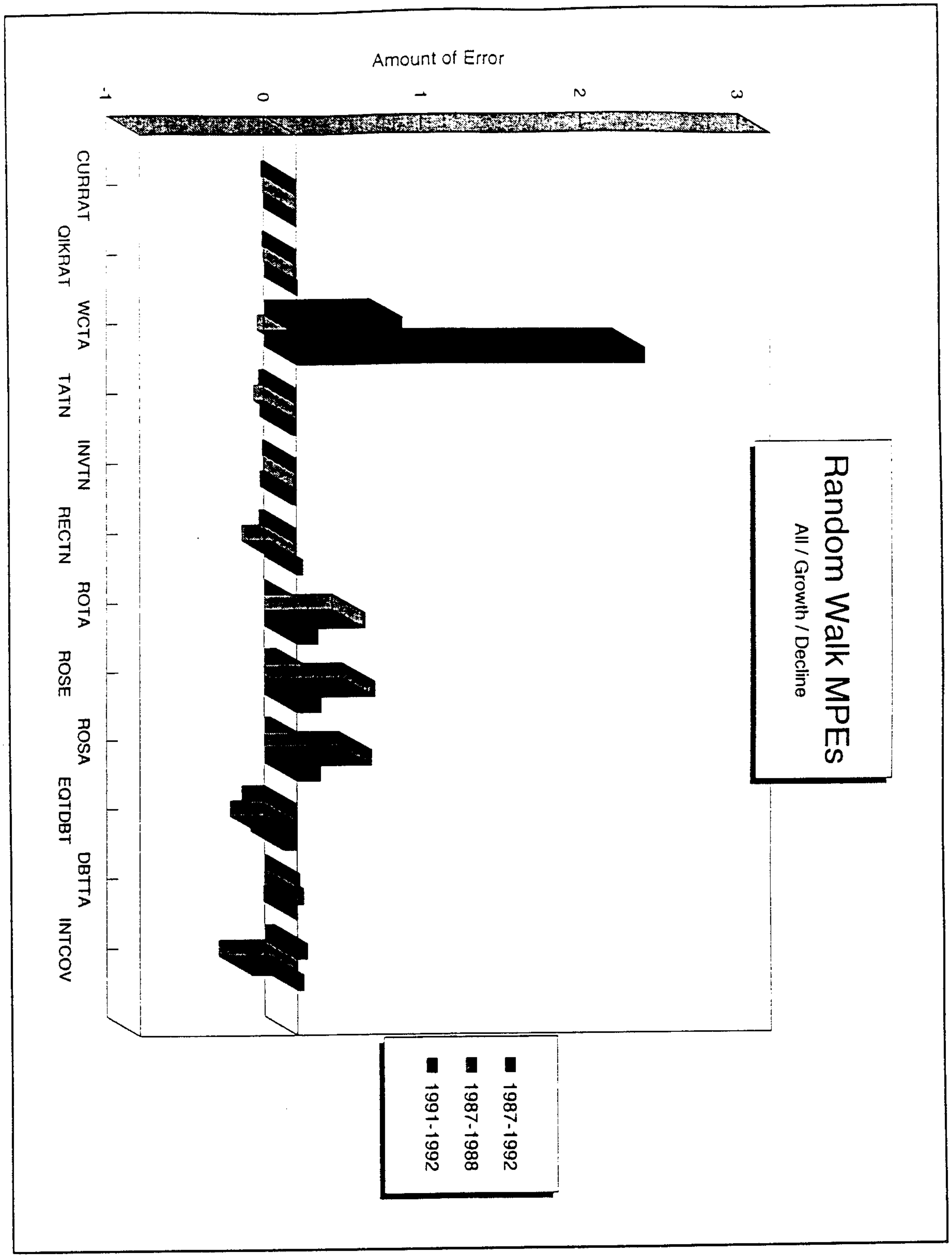

Figure 4.18 Comparison of Random Walk Forecast MPE in Periods of Industry Growth and Decline

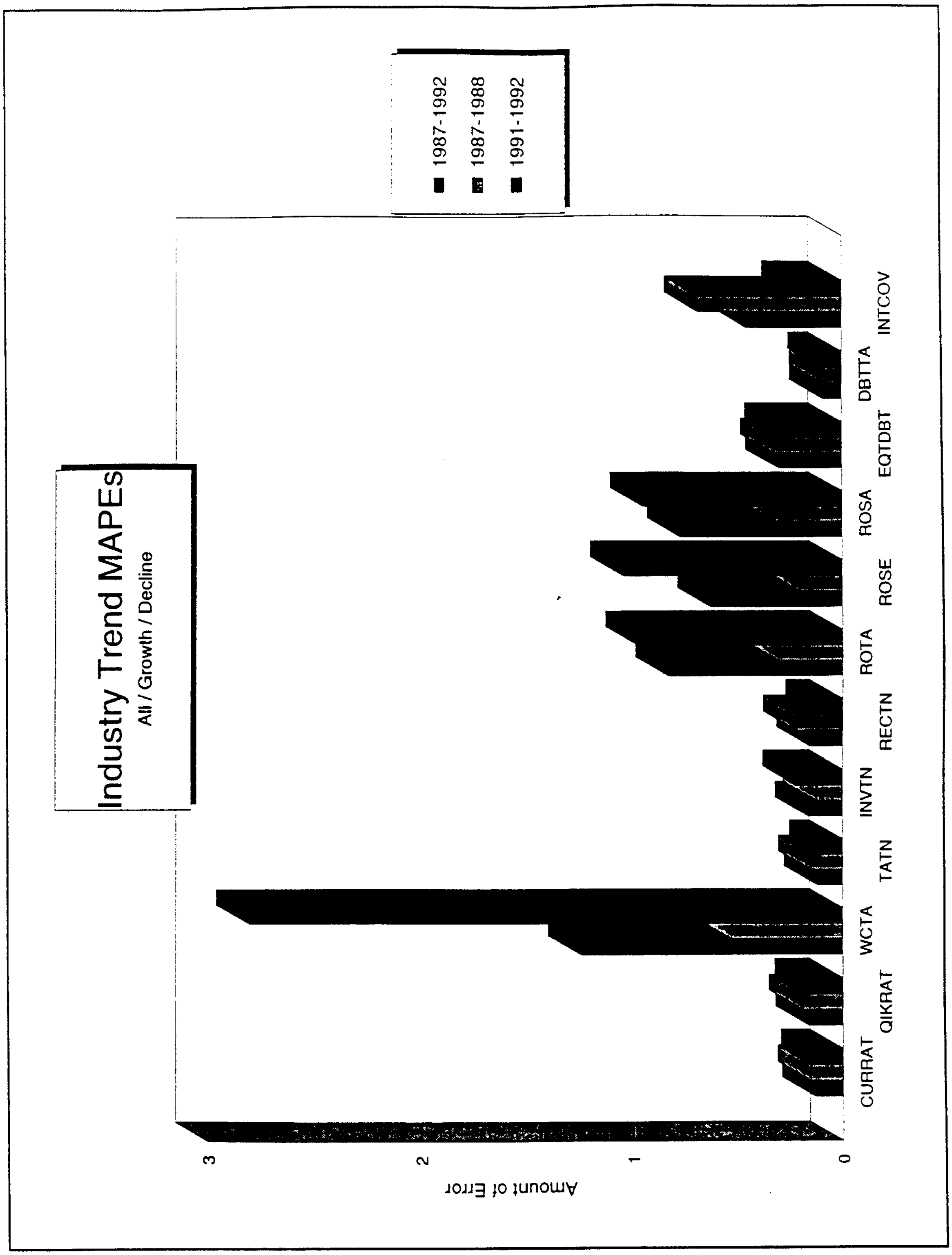

Figure 4.19 Comparison of Industry Trend Forecast MAPE in Periods of Industry Growth and Decline

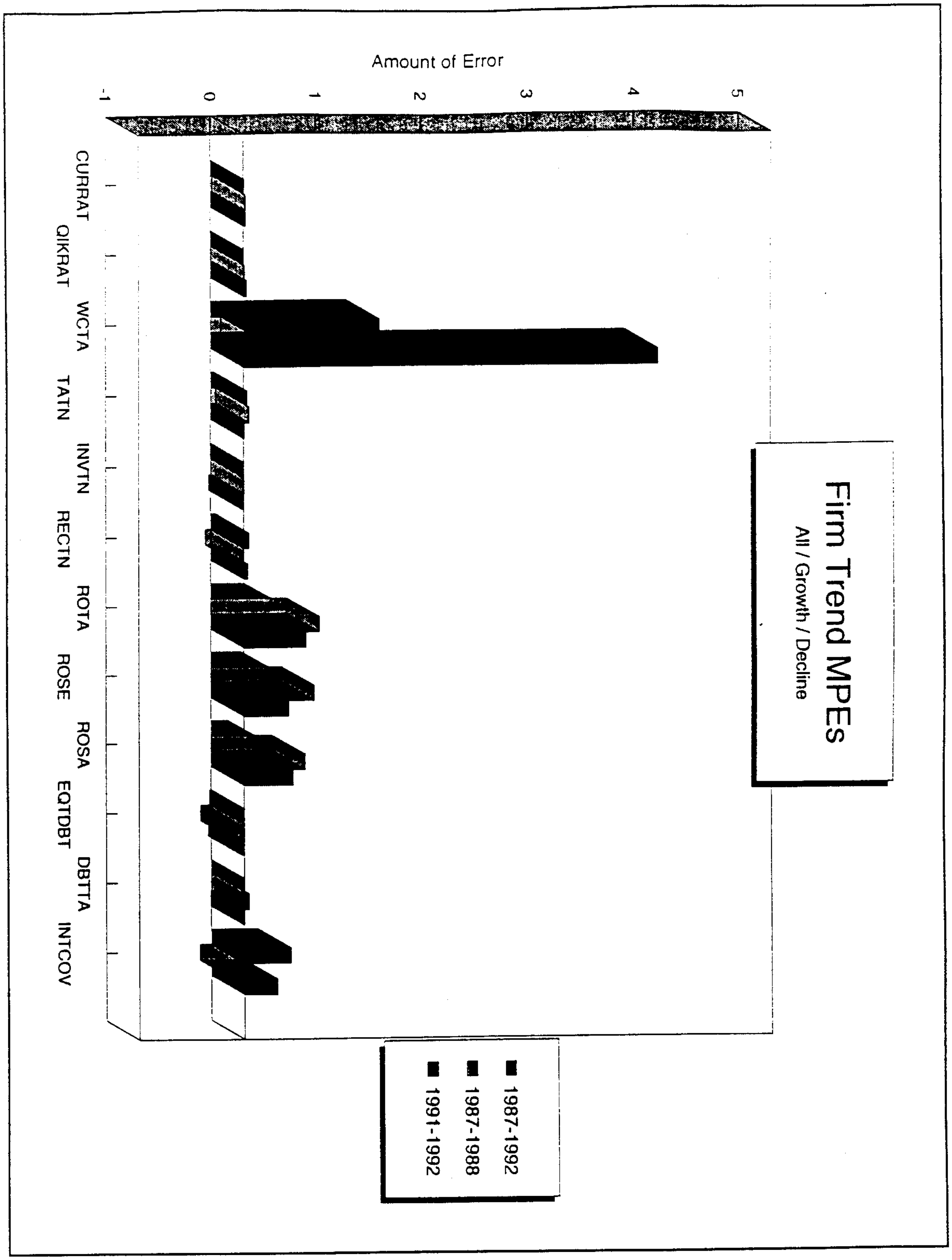

Figure 4.20 Comparison of Firm Trend Forecast MPE in Periods of Industry Growth and Decline

improved or degraded forecasting ability was similar for the other model forecasts.

Part of the reason for the inconclusive results may have been the short duration of the time periods used. Because the summary errors of forecasts were computed using only two year periods, small differences in a single forecast could affect these error values. The two year periods were probably inadequate to provide a satisfactory basis for comparing the growth versus decline model forecasting ability.

When comparing forecasting ability for periods of growth and decline, one clear distinction becomes apparent. For the models that had the worst forecasts over the entire period 1987 through 1992, the forecasting accuracy of these models was largely dependent on the health of the defense industry. For the working capital to total assets ratio, and the profitability ratios, the forecast from all models were much more accurate for the healthy industry years than for the years in which the industry was contracting. The MAPEs for these ratios were profoundly affected by the period of decline in the defense industry apparent in the latter half of the forecasts.

F. SUMMARY

The analysis of this thesis provided sufficient results to answer all of the thesis questions with the exception of the growth and decline forecast comparison. The analysis procedures and results also provide insight into several interesting areas not specifically outlined by the thesis questions listed in the first chapter. Additional discussions of ratio behavior and model forecasting ability brought to light through the analysis, as well as recommendations for improvements in future studies, and the final conclusions for this thesis are all contained in Chapter V.

V. CONCLUSIONS AND RECOMMENDATIONS

A. INTRODUCTION

The results listed in Chapter IV provided answers to the thesis questions posed in Chapter I. The general conclusions reached were that a low beta value is most appropriate for the partial adjustment models, that the trend models were best at minimizing bias, that the random walk model was best at forecasting in terms of both error measures, and that the simple industry average model was an implausible forecasting model. In addition, no model significantly outperformed the random walk for forecasting in all ratio categories.

The analysis also provides insight into several other areas of interest not addressed by the original thesis questions. These additional observations are discussed in the remainder of this thesis.

B. ADDITIONAL RATIO INSIGHTS

The most striking result of the model forecasting test results was that when one model was able to forecast a ratio with low bias and high accuracy relative to its own performance for other ratios, several other models obtained similar results. Forecasting ability therefore, was divided most distinctly by ratio rather than by model.

For example, the most accurate predictions, indicated by MAPEs under .20, were obtained for forecasts of the current, quick, total asset turnover, receivables turnover, and debt to total assets ratios. For these ratios' forecasts, the accuracy between the top four models varied by less than 1.5 percent. In addition, the top four models in terms of MAPE for these accurately forecasted ratios were always the random walk, industry trend, moving average adjustment, and fixed deviation adjustment, although not in this particular order. It was only for other ratios less accurately forecast that other models moved up in the relative MAPE ranking. It is interesting to note that the four models previously listed forecasted accurately across the different ratio categories that were used in this thesis organization.

This division of results by ratios, leads to the somewhat intuitively obvious proposition that some ratios are easier to forecast than others. It also leads to further questions. Are some ratios impossible to forecast accurately? Are some ratios uniformly easy to forecast regardless of economic conditions.

The forecast results obtained from 1987 through 1992 for the working capital to total assets ratio, and the profitability ratios, suggested initially that these ratios were simply hard to predict. High values for the MAPE were produced from all model forecasts. However the growth versus decline analysis provided a better picture to interpret. During the relatively healthy period of 1987 and 1988, these ratios were forecast much more accurately by all models than they were during the period of decline in the defense industry. Although models still did not forecast well for these ratios relative to most others during either period, the working capital to total assets and profitability ratios were much more predictable during the healthy period than during the period of contraction.

In contrast, the financial health of the defense industry seemed to have little effect on the ability of the models to forecast most of the other ratios. The two years of data for the two periods proved insufficient to answer the question regarding forecasting ability of models during periods of growth versus decline. However the results did clearly indicate that for the profitability and working capital to total assets ratios, the forecastability of the ratios was strongly affected for all models, and for most other ratios the ability to forecast model by model was not affected.

C. ADDITIONAL MODEL INSIGHTS

Attempts were made to group the results by model to obtain similar insights into the general predictive ability of the models. The results of the analysis were observed to see if models with certain components, i.e. models based on the industry performance versus models based on a firms own performance, performance of adjustment models versus trend models, etc. were uniformly better or worse. In fact, the content of the thesis questions pointed the analysis in this direction. However, other than the general observations already noted, no broad distinctions could be discerned between models across all ratio categories.

D. QUESTIONS FOR FUTURE ANALYSIS

The above insights make a strong case for future analysis to attack financial ratio model forecasting from a different perspective than that used by this thesis. Rather than posing questions simply in terms of what models are best at forecasting future values of financial ratios, or what models work best among traditional ratio categories, results from this thesis indicate that a better approach may be to phrase questions in terms of ratio predictability.

Such questions could include the following. What ratios can be forecast within a certain range of accuracy and bias, (for example an accuracy of less than 20 percent and a bias of less than 5 percent)? For these "forecastable" ratios, what models provide the best predictions of future value? Does the forecastability of the ratios combined with the type of models that predict these ratios well, provide evidence that firms can control these ratios? Or does it indicate that these ratios are inherently stable? Of the non-forecastable ratios, what are the common components? Is it possible to formulate new models that can take these common components into account and decrease the forecasting errors for these ratios? In periods of stability, growth, and decline, do specific ratios become more or less forecastable? What insights does this provide about the ratios or forecasting models?

E. APPLICABILITY TO DEPARTMENT OF DEFENSE ACTIVITIES

One of the primary reasons for carrying out this research was to attempt to provide addition information and methodology to Department of Defense analysts when evaluating private industry firms within the defense industries. Obviously, the research and results of this thesis provide only a small step toward making financial ratio forecasting models a viable tool for formal analysis. Continued research in this area, however, could eventually culminate in the creation of new tools and methods for financial evaluation of specific defense firms or industry segments. In addition, future research will certainly prove valuable by providing insight into defense firm ratio stability and behavior, as well as into defense industry financial trends in differing economic conditions

F. CONCLUSIONS

Model forecasting of the future values of financial ratios is an area that has been only sparsely covered in published research. This is surprising for many reasons. There are many types of financial ratio questions that could be answered through further forecasting research. Such research could provide insight into questions concerning: (1) model composition, (2) the ability of specific models to predict future ratio values, (3) the predictability of specific ratios, (4) the factors which can cause changes in ratio values over time, and (5) the validity of theories concerning the behavior of ratio time series. Forecasting future values of financial ratios has not been studied extensively, so there are many insights to be gained from even elementary studies using basic methodology and tools for analysis. Finally, financial ratio forecasting analysis involves predicting the future, (within the limited scope of financial ratio values.) Any attempt to predict the future inherently contains an element of surprise, which makes this analysis fun as well as interesting.

APPENDIX

This appendix contains a list of the 50 defense contractors whose financial reports were used to compile data for analysis.

FIRMS INCLUDED IN THE THESIS SAMPLE

1. McDonnell Douglas Corp.
2. Northrip Corp.
3. Lockheed Corp.
4. General Dynamics Corp.
5. General Electric Co.
6. Raytheon Co.
7. United Technologies Corp.
8. Boeing Co.
9. Martin Marietta Corp.
10. Grumman Corp.
11. Loral Corp.
12. AT&T Co.
13. Rockwell International Corp.
14. Westinghouse Electric Corp.
15. TRW Inc.
16. IBM Corp.
17. Unisys Corp.
18. ITT Corp.
19. Texas Instruments Inc.
20. GTE Corp.
21. Olin Corp.
22. Computer Sciences Corp.
23. FMC Corp.
24. Teledyne Inc.
25. Johnson Controls Inc.
26. Hercules Inc.
27. Motorola Inc.
28. Gencorp Inc.
29. Harris Corp.
30. Coastal Corp.
31. Honeywell Corp.
32. Harsco Crop.
33. Black & Decker Corp.
34. EG&G Inc.
35. Eastman Kodak Co.
36. Chrysler Corp.
37. CSX Corp.
38. E-Systems Inc.
39. Ford Motor Co.
40. General Motor Co.
41. Kaman Corp.
42. LTV Inc.
43. Morrison Knudsen Inc.
44. Dynamics Corp.
45. Allied Signal Inc.
46. Control Data Corp.
47. Hewlitt-Packard Inc.
48. Eaton Corp.
49. Trinity Industies Corp.
50. United Industrial Corp.

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